Impossible Probability:

Anthology,

Vol 5.

I doubt, therefore I exist.

Dr Ruben Garcia Pedraza

Preliminary Words for the Publication of *Impossible Probability, Anthology*, in Spanish:

Impossible Probability

The work presented here is a compilation of the posts I published on the blog *Impossible Probability* between 1 August 2011 and 13 January 2018, the posts I wrote in Spanish. From 13 January onwards, while living and working in London in different schools, and given the importance we already knew Global Artificial Intelligence was going to have, I would try to write them in English with the help of online correctors and translators, especially Google, and later I would use Grammarly.

The originals written in English, with all their imperfections, are still preserved on the *Impossible Probability* blog, and also on Internet Archive, where my poetic works can also be found.

As I have said on numerous occasions, especially in my poetry, behind every imperfection, behind every subtlety, entire hidden worlds are concealed, full of mystery and uncertainty yet to be discovered, and that the adventurous and hungry mind can find as easily as going to Internet Archive, where all my secrets await the right reader who knows how to translate them—like someone who by mistake finds a secret entrance, the passage leading to the cave where the elves who guard hidden knowledge dwell, and the dragons who defend the golden fortress.

While the original texts in English can be found on Internet Archive, the corrected and expanded version, this time using ChatGPT, can be found in scientific repositories (Zenodo, ORCID, PhilPapers) and on Amazon. In any case, if in the future a comparative study were carried out between my original texts in the *Impossible Probability* blog and Internet Archive, and the corrected and expanded versions, it would be clear without

any difficulty that the original contents are perfectly preserved, and the corrected and expanded versions are faithful to the contents we wrote together in 2018 in relation to Gaia, Mother, the Global Artificial Intelligence.

The importance of the documents that in this new series of books *Impossible Probability: Anthology* will be published in Spanish, containing the articles between 1 August 2011 and 13 January 2018, lies in the fact that we began to write this blog just a few weeks before the death of José Rodríguez Delgado, and a few months before the publication of our book *Introduction to Impossible Probability, Statistics of Probability and Statistical Probability.*

Although it is very difficult at the moment to explain who "we" are, and what *Impossible Probability* means for us, what matters is the work we leave: our work, our legacy, our *legend*, *our symbol*, our seal—independently of the judgment that history may later make of our contribution to the development of mathematics, Artificial Intelligence, and most importantly, Cyborg Psychology.

The first time we began to write about *Impossible Probability* I was only a student in the Faculty of Education at the Complutense University of Madrid [the Dean was Gonzalo Vazquez]. In my first year of university I had as professor Jesús Martín Ramírez, collaborator of Karl Pribram and author of the brain hologram theory, which is the origin of cyborg psychology. While José Delgado provided the structure, the stimoceiver, nevertheless, to understand the functioning of this technology in the 1970s and 80s, Pribram's contribution was fundamental—and even today it still is.

My first year of university was fabulous: good grades, good vacations hiking, summer camps in the mountains of Madrid—and suddenly, in the second year of university 1996–1997, my life would change abruptly, which can be seen in my poetry, how my poems began to acquire a more dramatic tone.

I repeated statistics in my second year, I repeated it at least three years, and I was even on the verge of being expelled from university. Miraculously, it did not happen, and precisely the last year I had left to pass statistics, I passed. The following year I would begin to write *Impossible Probability* as a critique of Karl Popper—and in a certain sense, it is.

Whereas for Karl Popper knowledge is false, only accepted provisionally as true until we refute it, in *Impossible Probability* rational knowledge is provisionally true while we investigate true pure knowledge—in the ultimate instance, our search for knowledge of the noumenon, which the human being cannot reach, hence the necessity of Global Artificial Intelligence: that machine capable of knowing what happens beyond human limitations.

What we call chaos, error, complexity, is only the noise produced by our human cognitive limitations, given our apriorism. The human being, limited both sensorially and cognitively, cannot know what really happens, but we can build the machine that can reach true knowledge of what happens—the truth in itself and for itself. That is, and no other, the true end of Artificial Intelligence: to reach the knowledge of truth, whatever it may be.

The path that takes me from my first works in *Impossible Probability* to Global Artificial Intelligence is not easy: much suffering, even despair, sometimes a sense of helplessness, a sense of abandonment—yet an inner force always pushed me forward. That inner force is what I call "we," although I understand that at this moment it is inexplicable.

Although I feel a bond that unites me to the *legend* of José Rodríguez Delgado, and which my Stockholm syndrome prevents me from understanding, my bond with Pribram is evident: Jesús Martín Ramírez. Pribram and Delgado worked at Yale University; probably only the skulls can say whether both were members of Skull & Bones, though there is no evidence to corroborate this.

Impossible Probability is a work that comes out of the romanticism of a student poet, who believed in white fairies, the rays of Zeus, and the light of the god Apollo illuminating the heart of every spirit and soul in a world full of mysteries and shadows.

It was from that world of poetry, in a country emerging from a failed transition, that the last survivor of the dream of reason would listen to his inner voice, dark and serene, and *Impossible Probability* would be born for the first time.

The first formulations of *Impossible Probability* date from 11 September 2001. My first formula would be the Impact of the Defect; then on 16 October 2002 the Second Method would appear, laying the foundations of the distinction between empirical and theoretical probability. I worked intensely until 2004. Between 2004 and 19 December 2009, I paused my mathematical frenzy, and it was not until 19 December 2009 when I returned, this time with the intention of publishing *Introduction to Impossible Probability, Statistics of Probability or Statistical Probability*, whose publication materialized just a few months after the death of José Rodríguez Delgado, although Delgado was able to see the first works published online in this *Impossible Probability* blog, which makes this blog a fundamental piece for understanding our work, our legacy, and most importantly—independently of our names, which matter little—the truly essential: our seed of the future, our eternal gratitude, a work of intelligence that will lay the foundations of the future technological society.

Dr. Rubén García Pedraza

20 August 2025, 19:00

Madrid, Villaverde

Preliminary Words for the English Version of *Impossible Probability, Anthology*.

Spanish-speaking readers have been able to enjoy our work since we began the foundational work of *Impossible Probability* in 2001, more precisely when we began to make it public in July 2011 through the *Impossible Probability* blog. The work presented here is an extended version of the posts published on the blog, an extended version translated into English with the help of Gepeto, my special GPT program.

In any case, a comparative study of the augmented translation presented here and the original works in Spanish could corroborate that the essential contents related to formulation and the philosophy of mathematics remain in accordance with the original electrical spirit of *Impossible Probability*.

The reason that obliges me to publish so hastily the English-language publication of all my works is the very complicated personal situation in which I find myself, due to serious mistakes committed by certain British institutions, which, completely blind to what our situation is, instead of having supported our program from the first moment, tried to sabotage it from the beginning through numerous obstacles and false loves.

I have no doubt that the manipulation to which I have been subjected by British institutions will one day be investigated, and at some point justice must make an appearance.

When that day comes, the first thing justice must recognize is the extreme difficulty and harshness of the conditions I have lived all my life since my earliest childhood. From the very day I came out of my mother's womb in Spain I have known nothing but pain and the oblivion of a society that prefers to look the other way and wash its hands, pretending that nothing is happening here. In the midst of the dictatorship of silence, I have had to survive all kinds of traps, deceptions, and attempts at assassination. The dictatorship of silence, the Roman circus, and the virtual zoo that my life has become will one day have to end. For this reason I beg the International Court of Justice that

when that day comes the matter be investigated down to the smallest detail, even being aware that in 48 years of savage dictatorship of silence I have developed Stockholm Syndrome. Under the harsh conditions in which I have had to learn to survive, if I have learned anything it is the importance of survival. I beg the International Court of Justice to understand what it means to survive 48 years of dictatorship living in a Roman circus full of traps and lions hidden in every corner.

I deeply regret having to publish my mathematical works under these conditions, and in record time doing all the translations I can, but at this moment I can only say that my life is at risk.

If one day I could testify before the International Court of Justice I beg you to understand the brutal complexity of the situation in which I have lived since the first minute I came out of my mother's womb. I have learned to survive.

Dr Ruben Garcia Pedraza

26 September 2025, 17:58

London, Leytostone

“La serie aleatoria de incoherencias sin lógica

Que en si mismo tiene sentido o

Forma de mensaje oculto”

“The random series of incoherences without logic

That in itself has meaning or

Form of a hidden message.”

Poem *Matematicas*

Ruben Garcia Pedraza

Written at Royal Albert Hall

London

Southbank

In memory of Pilar Bardem

Impossible Probability: Anthology, Vol 5.

Dr Ruben Garcia Pedraza

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41. Empirical Probability

41.1. General Definition of Empirical Probability

Empirical probability can be defined as the **actual statistical probability** of a subject or an option within a given study. Unlike theoretical probability, which is derived from abstract assumptions of equality or idealized models, empirical probability arises directly from **observable and measurable data**. It expresses the real and individual chances of a subject or option, calculated from the *direct score* or the *frequency of occurrence* that has been observed in the study.

Formally, the empirical probability of a subject or option is obtained by dividing the individual direct score or frequency by the total sum of all direct scores or frequencies of all subjects or options under consideration. In symbolic notation, the empirical probability of a subject or option is written as **p(xi)**, where *xi* represents the direct score or frequency of that particular subject or option. Thus, the formula can be expressed as:

$$p(x_i) = \frac{x_i}{\Sigma x_i}$$

where:

$x_i =$ direct score or frequency of the subject or option

$\Sigma x_i =$ sum of all direct scores or frequencies across all subjects or options

This definition establishes the empirical probability as a **relative proportion**: it is always contextual, as its value depends not only on the score of the individual element but also on the collective distribution of scores or frequencies within the entire sample. Hence, empirical probability is inherently comparative and systemic, reflecting the position of an individual subject or option in relation to the whole.

41.2. Empirical Probability in a Sample of Subjects

In the specific case of a study based on a **sample of subjects**, where each subject has been assigned a measurable direct score (such as test results, performance metrics, or behavioral indicators), the empirical probability represents the statistical probability associated with each individual. In this sense, empirical probability serves as a measure of the **true individual potential or capacity**, as determined by the observed performance of each subject when compared to the rest of the sample.

This approach is particularly useful when the aim of the research is not only to obtain an overall description of the group but also to highlight the **relative position** of individuals within it. The empirical probability, therefore, becomes a tool to distinguish variations, differences, or inequalities among subjects by converting raw scores into proportional values that can be directly compared within a statistical framework.

41.3. Educational Example of Empirical Probability

To illustrate this in the field of education, let us consider a study involving a group of students as the sample [of the possible universe of students with the same conditions]. After completing an assessment, such as an examination, each student receives a direct score equivalent to the grade obtained. In this context, the empirical probability of each student can be calculated as the ratio of their individual grade to the total sum of all grades obtained by the group.

For example, if a student achieves a grade of 80 out of a test, and the total of all students' grades sums to 1,200, the empirical probability of that student's result is:

$$p(x_i) = \frac{80}{1200} = 0.066 \ldots$$

This indicates that the student's performance accounts for approximately **6.7% of the overall distribution of results**. While the raw grade reflects only the student's individual achievement, the empirical probability situates this achievement within the broader performance of the group, making the result **statistically comparable** across subjects.

[Once we have this result we can study the Level of Bias and see the position of the student in relation to the theoretical probability, what it can be used as a predictive value in relation to future examinations, unless the student's behaviour changes]

41.4. Descriptive and Predictive Function of Empirical Probability in Education

The concept of empirical probability is not only descriptive but also predictive. From a descriptive perspective, it provides a faithful statistical representation of each student's performance, allowing researchers and educators to assess the **degree of mastery** or **level of knowledge** in the subject being evaluated. In this way, empirical probability transforms individual scores into comparable probabilities, enabling a more nuanced understanding of performance distribution.

From a predictive perspective, empirical probability can serve as a basis for estimating **future outcomes under similar conditions**. For instance, if a student has a certain empirical probability of success in one assessment, and no significant changes occur in their study habits, curriculum, or external conditions, one may reasonably predict that the student will exhibit a similar probability of success in subsequent assessments

of the same subject. Thus, empirical probability acts as a **statistical estimator of continuity**, projecting present realities into future expectations.

This dual function—descriptive and predictive—underscores the relevance of empirical probability in educational research and evaluation. It bridges the gap between immediate statistical measurement and longer-term inference, making it a versatile tool for both diagnosis and prognosis in the academic context.

[The prediction value of the empirical probability must be understood in relation to the theoretical probability, to determine positive or negative bias, or if all the students have similar results, equality. What we can determine given an initial empirical probability, in the first observation, is that, in absence of changes in the conditions or the context, the results of the student will be, within a margin of error due to changes in other students, the same level of bias or equality level. If in the second observation there is a change in the results beyond a margin of error, this should be attributed to changes in conditions, environment, or behaviours of the student]

41.5. Relationship with the Bias Level in Subjects

The **Bias Level** (*Nivel de Sesgo*) is a central concept that connects empirical probability with theoretical probability. For each subject within a sample—for example, a group of students in an educational context—the Bias Level is defined as the **difference between the empirical probability and the theoretical probability**. In formal terms:

$$\textit{Bias Level} = p(xi) - 1/N$$

where $p(x_i)$is the empirical probability of the subject, the **inverse of the sample size** (1/N) represents the theoretical probability, the inversion of N.

Within this framework, students who obtain **above-average grades** will have **positive bias**, meaning their empirical probability exceeds the theoretical expectation.

Conversely, students with **below-average grades** will show **negative bias**, since their empirical probability falls below the theoretical benchmark.

Students whose results approximate the **inverse of the sample size** (1/N)—will exhibit empirical probabilities close to the theoretical probability, resulting in a Bias Level tending toward zero. In this case, their performance is statistically aligned with the group's average expectation.

This relationship between empirical probability and Bias Level enables researchers to distinguish not only between relative achievements but also between **structural inequalities or advantages** within the group. Positive or negative bias indicates the direction of deviation from theoretical fairness, thereby providing a **quantitative measure of inequality** within the distribution of results.

41.6. Climatological Example of Empirical Probability

To extend the application of empirical probability beyond education, let us consider a **climatological study**. Suppose the units of analysis are the **twelve months of the year**, each associated with its **average monthly temperature**. In this context, the direct score of each month corresponds to its recorded average temperature, and the empirical probability of temperature for each month is calculated as the ratio of the monthly temperature to the sum of temperatures across all twelve months.

$$p(x_i) = \frac{\text{temperature of month } i}{\Sigma \text{ temperatures of all months}}$$

This approach allows us to interpret the temperature of a given month as a **relative proportion** within the annual cycle. For example, if July records very high average temperatures compared to other months, its empirical probability will be higher, reflecting the **greater contribution of July to the overall thermal distribution** of the

year. Conversely, months with lower average temperatures will have lower empirical probabilities, signaling their smaller role in the total distribution.

Thus, empirical probability provides a method to **quantify seasonal differences** in climate by translating absolute values (degrees) into relative statistical measures that can be directly compared across the yearly cycle.

[Once temperatures are transformed into empirical probabilities, applying the Bias Level we can study how temperatures differ from the theorical probability, and study differences in terms of negative and positive bias]

41.7. Descriptive and Predictive Function in Climatology

The function of empirical probability in climatology is both **descriptive** and **predictive**. Descriptively, it allows us to characterize the observed thermal behavior of each month. A low empirical probability value indicates that the month has contributed less to the annual thermal distribution—that is, it was a **cold month**. Conversely, a high empirical probability denotes a **hot month**, reflecting its higher-than-average contribution to the yearly temperature pattern.

From a predictive perspective, these values can also serve as indicators of **future tendencies**. For instance, if July consistently shows high empirical probabilities in historical data, one can reasonably predict that future Julys will also likely be warmer months, assuming no radical changes occur (such as those introduced by climate change). In this way, empirical probability acts as a **statistical estimator of climate patterns**, enabling researchers to project observed regularities into future expectations.

By combining descriptive and predictive functions, empirical probability in climatology becomes a crucial tool for both **understanding present conditions** and **anticipating future scenarios**, offering a probabilistic framework to complement physical and meteorological models.

41.8. Use of the Bias Level in Climatology

To refine climatological interpretation, the **Bias Level** can be employed as a criterion for classification. By comparing each month's empirical probability with its theoretical counterpart (1/N, where N = 12 months), we can establish a **statistical threshold** to determine whether a month should be considered cold, temperate, or hot.

- If the empirical probability is **below the theoretical value**, the month displays **negative bias**, and we classify it as a **cold month**.
- If the empirical probability is **above the theoretical value**, the month exhibits **positive bias**, and we classify it as a **hot month**.
- If the empirical probability is **close to the theoretical probability**, the month is considered ***temperate****, aligning with the average distribution*.

This classification system illustrates the versatility of the Bias Level as a quantitative indicator of deviation from equilibrium. It allows researchers to move beyond raw temperature values and adopt a **proportional and comparative lens**, situating each month's behavior within the broader systemic context of the annual cycle.

41.9. Studies of Subjects and Infinite Universes

The application of empirical probability extends into the theoretical framework of **universes of subjects**, which are conceptualized in Impossible Probability as **potentially infinite universes**. In such studies, subjects are associated with direct scores, forming samples that are part of a much larger universe. For example, a classroom of students may be considered a sample within the broader universe of all possible enrolled students.

Universes of subjects are termed **"universes of infinite subjects or options"** because, depending on the temporal framework, they can be **unbounded in scope**. Time may have:

- **No beginning and no end**, allowing infinite possibilities of measurement;

- **A beginning but no end**, generating an ever-expanding universe of potential observations;
- **Both a beginning and an end**, but with an **infinite number of instants within those boundaries**, producing the potential for an infinite number of measurements.

In all these cases, each measurement represents just **one among an infinite set of possible outcomes**. Thus, the universe of subjects is considered infinite in terms of its potential measurability, and empirical probability becomes a tool to **locate the finite within the infinite**—to establish proportional relationships even in contexts where the universe of study is theoretically unbounded.

This conceptualization underscores the philosophical dimension of Impossible Probability: empirical probability not only measures immediate, observable phenomena but also **interfaces with the infinite horizon of potential measurements**, situating the present instance within an open-ended continuum of possibilities.

41.10. Direct Score in Universes of Subjects

In universes of subjects, the **direct score** is the numerical result of measuring a particular quality or attribute in each subject of the sample. This quality must be **quantifiable**, meaning that it can be translated into a measurable magnitude, such as performance in a test, weight, income, or any other characteristic under investigation.

The **empirical probability** of a subject in such universes is then defined as the ratio of the subject's direct score for that quality to the sum of all direct scores across the sample:

$$p(x_i) = \frac{x_i}{\Sigma x_i}$$

Here, the direct score functions as the **individual contribution** of the subject to the total distribution. A higher direct score increases the subject's empirical probability, while a lower score decreases it.

In other words, the direct score is the **quantitative measurement of the intensity of a singular quality** in each subject. It provides the foundation for building empirical probability, since without measurement of direct scores there would be no basis for proportional comparison within the sample. Thus, universes of subjects rely fundamentally on **direct measurement** as the gateway to statistical representation.

41.11. Definition of Universes of Options

Alongside universes of subjects, there also exist **universes of options**. Unlike subjects, which are entities endowed with measurable qualities, options represent **possible alternatives in the face of an occurrence**. By definition, an option requires at least one other alternative to coexist simultaneously, since choice or resolution of an occurrence presupposes plurality.

In a sample of options, each option is a possible alternative, and statistical analysis determines the **total number of occurrences** of each option. This count is referred to as its **frequency**. The distinction is essential: while in universes of subjects what is measured is the *quality* of the subject, in universes of options what is measured is the *number of times* the option manifests in reality.

Universes of options are therefore **structurally finite**: they consist of a limited set of predefined alternatives (e.g., "heads" or "tails," "male" or "female," "party A" or "party B"), unlike universes of subjects, which can expand indefinitely depending on the temporal frame.

41.12. The Frequency of an Option

The **frequency of an option** is defined as the total number of occurrences in which that option has manifested in reality during the study. The **empirical probability of the**

option is obtained by dividing this individual frequency by the sum of all option frequencies observed in the sample.

In traditional statistics, the First Method, probability is defined as:

$$p(x_i) = \frac{f_i}{\Sigma f_i}$$

where f_i is the frequency of option i.

In the Second Method, as long as frequency and direct score are identical, the formulation of the empirical probability of an option is the same as the empirical probability of a subject: direct score or frequency divided by the sum of all direct scores or frequencies. In this case, applied to options: individual frequency divided by total frequency, where the symbols used are exactly the same as those used in the empirical probability for subjects.

$$p(x_i) = \frac{x_i}{\Sigma x_i}$$

In this sense, what traditional statistics calls **relative frequency**—that is, the frequency of an individual option relative to the total number of trials [f/Σf}—is precisely what Impossible Probability theory terms the **empirical probability of the option [xi: Σxi]**.

This reconceptualization is significant. By framing relative frequency explicitly as empirical probability, Impossible Probability places greater emphasis on the fact that such probabilities represent **real, observed possibilities of occurrence**. They are not abstractions or assumptions but **statistical reflections of reality**, grounded in actual manifestations of options within a given universe of study.

41.13. Example: Heads or Tails

Consider the case of tossing a coin into the air to study the probability of "heads" or "tails." The **sample of options** is composed of the two alternatives: heads and tails.

The empirical probability of heads is equal to the number of times heads appears divided by the total number of tosses (the sum of all heads plus all tails). Likewise, the empirical probability of tails is equal to the number of times tails appears divided by the same total.

$$p(\text{heads}) = \frac{f_{\text{heads}}}{f_{\text{heads}} + f_{\text{tails}}}$$

$$p(\text{tails}) = \frac{f_{\text{tails}}}{f_{\text{heads}} + f_{\text{tails}}}$$

Here, the **frequency of heads** is the count of occurrences where the coin lands on heads, while the **frequency of tails** is the count of occurrences where it lands on tails. Each empirical probability therefore measures the **real statistical possibility** of observing that option within the given experimental context.

This example demonstrates how empirical probability translates the raw counts of outcomes into **proportional measures**, making them comparable and meaningful in probabilistic terms.

41.14. Demographic Example: Male and Female

Another common application of empirical probability can be found in **demographic studies**. Suppose the aim is to estimate the probability of being male or female within a particular population. In this case, the **sample of options** is composed of two categories: male and female.

The empirical probability of women is calculated as the total number of women in the population divided by the total population size. Similarly, the empirical probability of men is the total number of men divided by the same population size:

$$p(\text{women}) = \frac{N_{\text{women}}}{N_{\text{total}}}, p(\text{men}) = \frac{N_{\text{men}}}{N_{\text{total}}}$$

This formulation measures the **real demographic proportion** of each category in the population. Unlike theoretical probability, which might assume equal distribution between men and women (50%–50%), empirical probability reflects the **actual statistical reality**, which may show deviations due to natural, social, or historical factors.

This example illustrates the importance of empirical probability in **capturing real-world distributions** rather than idealized assumptions. It is precisely in these contexts that Impossible Probability distinguishes itself from classical approaches by emphasizing the role of **observed data as the foundation of probability**.

41.15. Natural and Demographic Biases

In many cases of empirical probability, the assumption of **absence of bias**—that all options or categories should have equal probability—does not hold in reality. For instance, in the simple experiment of tossing a coin, theoretical probability assumes an equal distribution between heads and tails ($p = 0.5$ each). Likewise, in demographic terms, one might expect the probabilities of being male or female in a population to be approximately equal ($p = 0.5$ each).

However, **empirical observation often reveals deviations** from this ideal equilibrium. If a coin is physically biased—due to imperfections in its shape, weight distribution, or the way it is tossed—the empirical probability of heads may exceed that of tails, or vice

versa. In such cases, the option with greater observed frequency reflects a **positive bias**, while the less frequent option corresponds to a **negative bias**.

A similar principle applies in demographic studies. By natural and biological factors, which are inherently random in character, the probability of women in many populations is empirically observed to be higher than that of men. This constitutes a **natural bias**, not a product of deliberate manipulation but of **random variability rooted in natural processes**. Impossible Probability refers to this as a **random bias of chance itself**, acknowledging that even the most fundamental distributions may be affected by contingent asymmetries.

This example demonstrates how empirical probability not only captures **observed distributions** but also allows for the identification and quantification of **systematic deviations** from theoretical expectations, which is essential for understanding both experimental irregularities and natural demographic trends.

41.16. Example of Probability in Dice Rolls

Let us now consider the classic example of rolling a **six-sided die**. In this case, the universe of options consists of six possible outcomes, corresponding to the numbers 1 through 6. Each option is mutually exclusive and collectively exhaustive, meaning that every roll must yield exactly one of these six possibilities.

The **empirical probability** of any particular number, say "4," is calculated as the frequency with which that number appears divided by the total number of dice rolls:

$$p(4) = \frac{f_4}{\Sigma f_i}, i = 1 \dots 6$$

where f_4 is the frequency of the outcome "4," and Σf_i is the sum of the frequencies of all six outcomes, equivalent to the total number of rolls.

If the die is perfectly fair, repeated trials should tend toward an equal distribution of outcomes, approximating the theoretical probability of $\frac{1}{6} \approx 0.166\ldots$for each number. However, empirical probability reflects **actual results**, and in any finite set of trials, deviations will inevitably appear. By analyzing these deviations, one can evaluate whether the die behaves fairly or whether it exhibits **structural bias** favoring certain outcomes.

This case illustrates the essential feature of empirical probability: it is not merely a theoretical assumption but a **direct statistical measurement of observed frequencies**, sensitive to randomness, sample size, and potential irregularities in the system.

41.17. Electoral Example: Voting Intention

A particularly important application of empirical probability arises in the political domain, through **voting intention studies** in democratic systems. Here, the **options** correspond to political parties or candidates. Prior to an election, surveys are conducted to determine the number of respondents who intend to vote for each party.

The **frequency of intention to vote** for a party equals the number of respondents indicating preference for that party. The **empirical probability of voting intention** for the party is then calculated as:

$$p(\text{party}_i) = \frac{f_i}{\Sigma f_i}$$

where $f_i$is the frequency of voters supporting party i, and $\Sigma f_i$is the total number of respondents in the survey.

This probability provides a measure of the **real statistical chances** of electoral success for each party within the surveyed population. Parties with empirical probabilities approaching the **Maximum Empirical Probability Possible** ($p(x_i) = 1$) are those with the greatest likelihood of winning, reflecting their **positive bias** (empirical probability higher than theoretical expectation). Conversely, parties with empirical probabilities closer to the **Minimum Empirical Probability Possible** ($p(x_i) = 0$) are those least likely to succeed, carrying **negative bias**.

Thus, empirical probability translates survey data into **quantifiable measures of political viability**, distinguishing between strong, moderate, and weak parties in terms of their statistical position relative to theoretical equilibrium.

The preceding examples—coin tosses, dice rolls, demographic proportions, and electoral surveys—illustrate a common structure. In all these cases, the **universe of options** is **finite and predetermined a priori**. That is, the possible outcomes are known in advance and limited in number (e.g., two outcomes in a coin toss, six in a die roll, two in a demographic binary, or a finite set of political parties).

This distinguishes universes of options from **universes of subjects**, which may tend toward infinity depending on the temporal or conceptual frame. In Impossible Probability, universes of options are therefore designated as **"limited option universes"**, emphasizing their bounded nature and the fact that empirical probability in such contexts operates over **closed sets of alternatives**.

41.18. Universality of Empirical Probability

Whether we are dealing with a **universe of subjects**, where direct scores are obtained by measuring the intensity of a particular quality, or with a **universe of options**, where frequencies of occurrence are counted, the principle remains universal: in *Impossible Probability*, the **empirical probability of any subject or option** is always defined as the **individual direct score or frequency divided by the sum of all direct scores or frequencies**.

$$p(x_i) = \frac{x_i}{\Sigma x_i}$$

This general formulation applies across contexts. If the focus is on **subjects**, empirical probability expresses the ratio between the subject's direct score and the total of all direct scores in the sample. If the focus is on **options**, it expresses the ratio between the option's frequency and the total of all frequencies observed.

In both cases, empirical probability represents a **real statistical probability**, because it derives directly from empirical measurement—either of direct scores or of frequencies. It thus reflects the **actual, observable possibilities** of the subject or option within the sample, regardless of whether that sample comes from a universe of potentially infinite subjects or from a finite universe of predetermined options.

This universality is one of the defining strengths of Impossible Probability: it establishes a **single, coherent definition of empirical probability** that is applicable to diverse domains of knowledge, ensuring that all measurements—whether educational, demographic, climatic, or political—can be understood within the same proportional framework.

41.19. Descriptive and Predictive Functions

The empirical probability of a subject or option has two fundamental functions: **descriptive** and **predictive**.

1. **Descriptive function**: Empirical probability provides a **faithful statistical description** of a subject or option's position within the distribution at the moment of measurement. It converts raw data (scores or frequencies) into

relative probabilities, allowing researchers to compare individuals or alternatives not in absolute but in proportional terms.

2. **Predictive function**: Empirical probability also operates as an **a priori indicator of future outcomes**, under the assumption that conditions remain stable. That is, given the current empirical probability of a subject or option, one can infer what its likely behavior will be in subsequent observations. For example, if a subject consistently shows high empirical probability in current evaluations, it is reasonable to predict continued success under similar circumstances.

This dual functionality underscores the **epistemological importance** of empirical probability. It bridges the present and the future: what is measured in the present not only describes reality but also projects itself as a probabilistic expectation into the future. In this sense, empirical probability is not only a tool of representation but also a tool of anticipation.

41.20. Applied Example in Education

Consider once more the case of an educational study. Suppose we have a group of students who have completed an exam, and we calculate their empirical probabilities based on their respective grades. These values immediately provide a **descriptive profile** of the group: students with higher empirical probabilities are those who performed above their peers, while those with lower values are below average.

But the value of empirical probability extends further. If we assume that each student maintains the same study habits, learning environment, and external conditions, then these empirical probabilities can also be interpreted **predictively**. Students with higher probabilities are expected to continue obtaining high grades, while those with lower probabilities are expected to continue struggling.

Of course, this predictive role must be handled with care. A responsible teacher, upon observing the predictive implications of empirical probability, will not treat these values as deterministic but as **signals of where intervention is needed**. The empirical

probability highlights which students have fewer chances of success under current conditions, thereby providing a rational basis for targeted pedagogical action.

Nonetheless, in the absence of any change, empirical probability serves as a **strong a priori estimator** of performance. Its power lies in the fact that it translates immediate outcomes into statistically grounded forecasts, connecting the reality of present results with the probability of future scenarios.

[In an educational scenario, the ideal would be that all students obtain high grades, so their empirical probability should be around the inversion of N. In this case, equality should be considered the pedagogical target.]

41.21. Applied Example in Climatology

If the **average monthly temperature** remains constant over time, then the **empirical probability of temperature for each month** functions as an *a priori* estimate of the real possibilities of temperature in future years. In other words, the proportional contribution of each month to the overall annual temperature distribution allows us to forecast the **statistical likelihood of hot or cold conditions** repeating in subsequent years.

This predictive role of empirical probability is valid only under the assumption of **stability in external conditions**. If a disruptive phenomenon such as **climate change** significantly alters the long-term behavior of monthly temperatures, then the predictive value of past empirical probabilities diminishes. In such cases, deviations between past distributions and future outcomes highlight the influence of exogenous factors on empirical models.

Thus, empirical probability in climatology not only provides a **snapshot of current patterns** but also emphasizes the **conditionality of predictions**: they are valid only insofar as the underlying structural conditions of climate remain unchanged.

41.22. Demographic Example

In demographic studies, empirical probability offers a straightforward yet powerful predictive tool. Suppose a statistical analysis shows that the probability of being female in a given society is greater than that of being male. If the **demographic pyramid** remains stable—meaning no significant shifts occur in birth rates, mortality rates, or migration flows—then it is reasonable to infer, *a priori*, that this imbalance will persist into future years.

In such a case, the empirical probability of women being greater than that of men is not merely a **descriptive measure** of the present moment but also a **predictive indicator** of the likely demographic structure in the near future. This dual role demonstrates how empirical probability connects **static representation** (the measurement of current reality) with **dynamic inference** (the projection of future states), reinforcing its role as a methodological bridge between the present and the future.

41.23. Electoral Example

In the political sphere, empirical probability is especially relevant in the context of **election forecasting**. Consider a survey conducted shortly before an election:

- One party shows the **maximum empirical probability**, denoted $p(x_i^+)$.
- A second party shows a probability **close to the theoretical probability**, denoted $p(x_i \approx)$.
- A third party shows the **minimum empirical probability**, denoted $p(x_i^-)$.

Unless the parties with lower probabilities undertake **substantial strategic interventions** capable of altering the distribution of voter preferences, the most likely outcome is that the party with maximum empirical probability will win the election and obtain the presidency. The party with probability close to the theoretical average will

secure moderate results, while the party with minimum empirical probability will end up with the weakest representation.

This example illustrates the **predictive capacity of empirical probability** in electoral studies. It is not deterministic but probabilistic: it identifies the **most plausible scenario** given the current distribution of intentions, while leaving open the possibility of change if conditions or strategies shift before the actual election.

41.24. Dual Descriptive and Predictive Function

The empirical probability of a subject or option always operates with a **dual function**:

- **Descriptive**, because it provides a statistical representation of real possibilities at the precise moment of measurement.
- **Predictive**, because, under conditions of stability, it allows us to estimate what those possibilities are likely to be in the future.

This duality is what grants empirical probability its **epistemological strength**. It simultaneously grounds us in the reality of the present while projecting a probabilistic horizon into the future. The two functions are inseparable: description and prediction are two sides of the same methodological coin.

41.25. Relativity and Proportionality of Empirical Probability

Empirical probability is inherently **relative and proportional**. For the empirical probability of any subject or option to remain constant, it is necessary that the probabilities of all other subjects or options in the sample remain constant as well.

If the empirical probability of even one subject or option changes, then—due to the proportional nature of the calculation—the empirical probabilities of all others will also be affected. This is because the denominator in the formula (Σx_i) changes whenever any individual frequency or direct score changes, thereby altering the proportional weight of all elements simultaneously.

This systemic interdependence makes empirical probability a **relational statistic**: it cannot be understood in isolation but only within the context of the full distribution. A change in one element reverberates throughout the entire probabilistic structure.

41.26. Systemic Nature of the Empirical Model

The systemic character of empirical probability means that it is not merely a **collection of independent measurements** but rather a **dynamic network of interrelated proportions**. A single alteration in the behavior of one subject or option implies a transformation in the overall behavior of the entire sample.

This characteristic situates empirical probability within the logic of **complex systems**: it is sensitive to local variations that generate global consequences. It reflects the idea that reality is structured not as a set of isolated phenomena but as a **web of proportional relations**, where the part always influences the whole.

[One of my most influential theories while working on this blog was the butterfly effect. Now, in London, the butterfly effect could be renamed the snowball effect: any single alteration or change in the most seemingly meaningless situation could trigger complex scenarios of chain reactions of cause and effect, from local to global. Right now, London is the perfect case study for examining social complex systems.]

41.27. Types of Studies in Impossible Probability

In *Impossible Probability*, different types of studies have been distinguished depending on the methodological focus:

- In **Chapter 10**, the text details various forms of **intrameditional inferential studies**, which establish relationships within a given set of data.
- In **Chapter 11**, it introduces the different **models of rational criticism** based on the object of study, applying empirical probabilities within the framework of the **Second Method of statistical probability**.

- In **Chapter 12**, it presents rational criticism models adapted specifically to **direct scores or frequencies**, highlighting the versatility of the approach in handling both subjects and options.

Together, these classifications reveal that empirical probability is not only a statistical construct but also the foundation of a **comprehensive critical methodology**. *It is a tool not just for describing data but for interrogating it, testing its validity, and situating it within broader epistemological frameworks*.

41.28. Normal and Omega Studies

Within the taxonomy of studies in *Impossible Probability*, it is important to distinguish between **normal studies** and **omega studies**.

- **Normal studies** include several subtypes:
    - **Equality of opportunities**: where the empirical probabilities tend toward the theoretical probability, defined as the inverse of N (1/N).
    - **Positive bias studies**: where, within the total N, there exists a single subject or option that is considered ideal, and the goal is to maximize its empirical probability. In the limit, this ideal tends toward the **Maximum Empirical Probability Possible**, that is p(xi)=1.
    - **Negative bias studies**: where the ideal is the minimization of probabilities. This can occur in two forms:
        - The **zero-sample ideal**, where the empirical probability of all subjects or options is reduced to zero, such as in the eradication of diseases (probability of illness = 0) or errors (probability of error = 0).
        - The **minimum-reduction ideal**, where, among N subjects or options, certain ones are targeted to reduce their empirical probability as close to zero as possible.

- **Omega studies**, by contrast, are cases where, given N, there exists a **subset of ideal subjects or options**, fewer than N but equal to or greater than two. These models require a different treatment because, unlike normal studies, the ideal is not maximum or minimum dispersion but rather an **ideal dispersion**. In other words, while normal models treat extremes (all concentrated in one option, or all reduced to zero), omega models focus on balanced subsets within the distribution.

41.29. Variations in Subjects and Options

Because empirical probability is inherently **relative and proportional**, any manipulation of the **independent variable**—whether by experimental [or quasi experimental] intervention or by natural variation—has systemic consequences. ***Even the smallest change in the direct score or frequency of a single subject or option produces automatic changes in the entire distribution of empirical probabilities.***

This sensitivity underscores the interconnectedness of the model. The empirical probability of one element cannot be altered in isolation, since the proportional structure ensures that all other probabilities shift accordingly. This makes empirical probability a powerful diagnostic tool for detecting the systemic effects of local changes.

41.30. Effect of Increases in Direct Scores

Suppose in a study that one subject or option increases its direct score or frequency, while all others remain constant. The immediate result is that the **sum of all direct scores** increases. Consequently, the empirical probability of the subject or option that increased its score rises, while the empirical probabilities of all other subjects or options decrease.

This occurs because, although their absolute scores remain constant, the denominator of the probability formula (Σx_i) has increased, thereby reducing their proportional

contribution to the total. In short, **the growth of one reduces the relative weight of the rest**.

This effect illustrates a fundamental principle: empirical probability measures **relative presence, not absolute magnitude**.

41.31. Effect of Reductions in Direct Scores

Conversely, if one subject or option reduces its direct score or frequency, its empirical probability decreases. However, because the total sum of direct scores also decreases, the **relative weight of all other subjects or options increases**, even if their absolute scores remain unchanged.

Thus, empirical probability demonstrates how the **decline of one element benefits the others** proportionally. This reciprocity is an intrinsic feature of the model, highlighting once again the relational and systemic nature of empirical probability.

41.32. Direct and Indirect Variations

The variation of empirical probability can occur through two distinct mechanisms:

1. **Direct variation**: When the score or frequency of a subject or option changes, its empirical probability increases or decreases directly as a result.
2. **Indirect variation**: When the sum of all scores or frequencies changes, the empirical probability of any element may increase or decrease, even if its individual score or frequency remains constant.

Thus, empirical probability is sensitive not only to **individual changes** but also to **collective fluctuations**. At constant individual scores, probabilities rise when the total sum decreases and fall when the total sum increases. This dual pathway of variation illustrates the **complex dynamics of proportional systems**.

41.33. Relationship Between Samples and Dispersion

In empirical probability studies, it is necessary to distinguish between two different samples:

- The **sample of subjects or options**, represented as N.
- The **sample of direct scores or frequencies**, represented as Σx_i.

For a sample of N subjects, the sample of direct scores is the sum of all their measured qualities. For a sample N of options, the sample of frequencies is the total count of occurrences across all options.

This dual sampling is essential because the **dispersion of empirical probabilities** depends not only on N (the number of elements) but also on the magnitude and distribution of their scores or frequencies. The interaction between these two samples forms the foundation of statistical dispersion analysis within the framework of Impossible Probability.

41.34. Factors of Dispersion and Object of Study

Dispersion in empirical probability is influenced by multiple factors:

- **Experimental [or quasi experimental] manipulation**, which can deliberately alter the distribution of scores or frequencies.
- **The size of N**, since larger or smaller sample sizes affect the granularity of probabilities.
- **The magnitude of the score or frequency sample**, which determines the proportional weights assigned to each subject or option.

These factors are analyzed within the broader relationship between **empirical dispersion** (the distribution observed in practice) and **theoretical dispersion** (the

expected distribution under idealized conditions). The interplay between the two reflects the **dual dimension of reality** in Impossible Probability: empirical (what occurs) and theoretical (what is expected). Together, they constitute the true object of study of probability science.

[The reason I highlight all the time the difference between experimental and quasi experimental is due to the fact that under experimental conditions, laboratory conditions, all the variables are under absolute control, but in quasi experimental conditions not all variables comply with laboratory conditions, normally quasi experimental research is more frequent in social studies under real conditions.]

41.35. Final Synthesis on Empirical Probability

In synthesis, probability is fundamentally the **study of what happens**. Through this study, we establish proportions or statistical probabilities, which may be **empirical**, **theoretical**, or **critical**.

- **Empirical probability** derives from the actual data of the sample and reflects the real possibilities of subjects or options.
- **Theoretical probability** derives from assumptions of *ideal distribution* and functions as a benchmark of equality or fairness.
- **Critical probability** (as developed in Impossible Probability) arises from the rational *analysis of deviations* between the empirical and the theoretical, *seeking to evaluate the significance of bias*.

Empirical probability, therefore, serves as the **bridge between measurement and meaning**. It not only describes reality as it is observed but also provides the *foundation for statistical prediction of behavior and tendencies*. In this way, it becomes both a **descriptive mirror of the present** and a **predictive instrument for the future**, central to the methodology of Impossible Probability.

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42. Scientific Policy

42.1. Historical Debate and Antinomies

When the debates and philosophical discussions throughout history about whether science is neutral or, instead, ideological and political are examined closely from a historical perspective, two positions appear in persistent opposition—very much in the spirit of **Kantian antinomies**. That is, one can clearly distinguish two contrary theses regarding the same question, each internally coherent within its own scientific model and the logical sequence of arguments that supports it, yet mutually contradictory.

Calling these positions "antinomies" emphasizes that the conflict is not merely empirical but **structural**: each side deploys a chain of premises, methods, and criteria of validity that render its conclusions rational within its own framework. Thus, disputes about scientific neutrality are not simply disagreements about facts; they are disagreements about **what counts as an admissible reason**, what methods ought to bind inquiry, and what the *telos* of science should be (truth, emancipation, prediction, technological control, public good, etc.). Historically, this antinomic structure resurfaces across epochs—from early modern quarrels about natural philosophy and theology, through nineteenth-century disputes over positivism and its critics, to twentieth-century arguments between logical empiricism, critical rationalism, phenomenology, Marxism, and post-positivist philosophies of science. The **recurrence** of the opposition suggests that neutrality vs. politicization is not a contingency of one period but a **constitutive tension** within scientific modernity.

42.2. Two Irreconcilable Tendencies

Particularly since the dawn of modernity, the question of science's neutral or ideological–political nature has crystalized into two seemingly irreconcilable philosophical tendencies. On one side are those who defend the **neutrality of science** over and against any subjective valuation. On the other side are philosophies that insist upon the **distinctly political and ideological character** of science.

The first tendency grounds the authority of science in **methodological objectivity**—standardization of observation, replicability, intersubjective testability, and mathematical formalization—so that cognitive claims can be insulated from partisan commitments. The second tendency argues that science is **inescapably situated**: research agendas, funding priorities, problem framings, categories of analysis, and criteria of significance are embedded in social structures, value commitments, and institutional power. Hence, for this view, "neutrality" can function as a **mask** that conceals the upstream choices that shape what becomes visible as a scientific problem in the first place. The resulting opposition is not merely rhetorical: it concerns whether **normativity** (ethical–political aims, interests, or worldviews) is external to science or **constitutive** of it.

42.3. Arguments for Scientific Neutrality

Philosophical models that defend scientific neutrality advance a logically connected set of reasons which, taken as a series of premises culminating in conclusions, are valid within their framework. Since science grounds its results in **objective investigation**, it ought, morally and epistemically, to stand **above ideological and political disputes**, which are taken to be subjective. Consequently, the truths of science should prevail over partisan or ideological opinion; science must therefore safeguard its **independence** from political–ideological influence. This alleged **moral supremacy** of

scientific propositions over ideological assertions follows from science's greater objectivity: political or ideological valuations lack scientific foundation insofar as they rest on mere opinion. Hence, science is said to be free of political or ideological bias; its neutrality makes it a more faithful guide to reality than political or ideological judgments. Scientific claims—founded on objectivity and methodological rigor—ought to remain beyond suspicion of ideological manipulation or interpretation; the ideal is a **pure, neutral science**. The moral superiority of science over subjective political or ideological interpretation is attributed to the **purity of scientific morality**, understood as free from partisan, political, ideological, or subjective interests. Science's sole aim is **pure truth**, and the purity of truth is the only genuine guarantee of a correspondingly **pure morality**.

Elaborated more fully, neutrality arguments typically rest on four pillars:

1. **Epistemic autonomy:** scientific methods (controlled observation, experimental design, statistical inference, peer review) are designed to **filter out** interest-laden distortions, making results responsive primarily to evidence.
2. **Public objectivity:** because results are replicable and methods transparent, claims become **intersubjectively checkable**, curbing the authority of private belief.
3. **Normative minimalism:** science seeks **truth-apt descriptions and explanations**, not comprehensive doctrines of the good; therefore it restrains itself from prescribing values, which preserves a domain where **disagreement can be resolved** by evidence rather than ideology.
4. **Institutional insulation:** autonomy from political control and partisan funding criteria is viewed as a **precondition** of reliable inquiry; otherwise, incentives would skew what is studied and how it is concluded.

Within this logic, neutrality is not indifference but a **discipline of self-limitation**: science binds itself to procedures that minimize subjective interference, thereby underwriting both its **moral authority** (because it does not serve factional interests) and its **epistemic authority** (because it reliably tracks facts). The claim that the pursuit

of **pure truth** grounds a **pure morality** reflects a further thesis: if moral decisions are to be just, they must be informed by **uncontaminated knowledge**. Thus, neutrality is portrayed as an ethical requirement of any polity that aspires to govern by reasons rather than by will or ideology.

42.4. Thesis of the Intrinsic Politicity of Science

In contrast to those philosophical models that defend a pure and neutral science, independent of all subjective political or ideological evaluation, there are opposing models that affirm the **absolutely political or ideological nature of science**. According to these perspectives, by definition, all science is political.

This position does not regard politicization as a corruption of scientific practice, but as an **essential feature** of what science is. The very act of selecting research problems, deciding what questions are meaningful, prioritizing methodologies, and interpreting results is always entangled with values, interests, and institutional structures. Hence, science is never a detached mirror of nature but a **socially situated practice** embedded in broader political–economic systems. From this standpoint, the claim to neutrality is not only illusory but potentially dangerous, as it can conceal the structures of power and ideology that shape knowledge production. In short, science is political not merely by accident but by essence, because it is a **human practice generated within political communities**.

42.5. Traditions that Defend Neutrality

Throughout the history of philosophy, various schools have championed the idea of a science free from political or ideological connotation or manipulation—a **neutral and pure science**. These include **empiricism and materialism, rationalism and critical rationalism, positivism and neo-positivism**. All of them shared, despite their differences, a commitment to the **scientific utopia of a pure truth**, grounded in a scientific morality superior to subjective ideological or political influence. For these

traditions, **scientific neutrality** was the only possible guarantee of the moral purity of scientific statements.

The neutralist traditions emphasize that the epistemic authority of science depends on its **separation from partisan interests**. Empiricism valorizes direct observation and experience; rationalism defends the autonomy of reason; critical rationalism stresses the role of falsifiability; positivism and neo-positivism rely on logical analysis and verification. Despite their methodological differences, they converge in seeing **purity of method** as both an epistemic and a moral safeguard. Their shared ideal is that scientific claims can achieve a **supra-political universality**, valid regardless of cultural or ideological context. This vision underpins much of the modern ideal of science as the **arbiter of truth**.

42.6. The Moral Foundation of Pure Science

The moral purity of science—the very moral ground that supports the idea of pure science—was thought to rest on the capacity of scientific propositions to be **demonstrated through collections of data, empirical facts, or scientific proofs**. Within this framework, the hypotheses upheld by science, being demonstrable independently of political or ideological manipulation, were regarded as truths in and of themselves.

The notion here is that **evidence confers moral legitimacy**. A claim that can be replicated and confirmed through observation or experiment carries with it not only epistemic credibility but also a kind of **moral authority**, because it is not dependent on personal belief or partisan interest. This underpins the vision of a **science above politics**, capable of producing universally valid truths. The strength of this position lies in its insistence that only by detaching science from ideology can we guarantee the purity of truth—and that only **pure truth** can serve as the foundation for a truly **pure morality**.

42.7. Idealist Critique and the Marxist Turn

Against the supposed immaculate moral purity of the theories defending science's neutrality, stand the philosophical theses that insist that **all science is political**. While many philosophers, especially from the **idealist tradition**, had already questioned the political and ideological independence of science (since it depends on human ideas, which are never completely free of subjective values), the most critical stance emerged in the **nineteenth century** with **dialectical materialism**. Initiated by **Marx and Engels**, and drawing upon Hegelian dialectics, this school highlighted the **inseparability of philosophy, science, and politics**.

In Hegel, political idealism and scientific idealism were intimately linked: philosophy and science were both mobilized to defend the ideals of the state and its cultural system. By adapting Hegel's dialectics to materialism, Marx and Engels developed a new critical perspective that foregrounded how every scientific discourse **carries within it a political or ideological discourse**. Thus, science was not a sphere of neutrality but a terrain of struggle, shaped by and contributing to the material conditions and ideological frameworks of society.

[While Marx and Engels have been regarded as the first authors to debate publicly the importance of politics and ideology in the scientific building, their ideas in fact are not new. The way in which the Prussian State played a pivotal role in Hegel and other idealist philosophers, linking philosophy to religious politics—especially after the Reformation of Martin Luther and John Calvin—is a clear example that the debate on how politics and religion shape science and philosophy was an important topic since 1517. But this debate could be traced back even earlier, for instance, to Hypatia of Alexandria.]

42.8. Twentieth-Century Developments: The Frankfurt School

Dialectical materialism was profoundly developed in the twentieth century, particularly by the **Institute for Social Research**, better known as the **Frankfurt School**. This

intellectual movement elaborated a **critical social theory** that emphasized the political and ideological influences permeating science. Thinkers such as Horkheimer, Adorno, and Marcuse, and later Habermas, argued that science is not autonomous but deeply implicated in systems of domination, culture, and ideology.

The Frankfurt School's project was to reveal the **hidden power structures** that scientific rationality can both expose and reproduce. For them, critique was not external to science but a necessary dimension of understanding its social role. Habermas, one of the most influential contemporary inheritors of this tradition, advanced a theory of **communicative rationality** and **critical social philosophy**, insisting that science and technology must be examined in terms of their political implications and their role in shaping public life. The Frankfurt School thus ensured that the critique of neutrality—and the affirmation of the politicization of science—remains a **living current in contemporary philosophy of science**, with enduring influence across the humanities and social sciences.

[While I was working on this blog, my thesis was quite different from postmodern theories. Even though I have been reading about AI all my life, and at some point my tendencies could be defined as post-humanist and post-industrialist, within the theories that debate how ideology and politics shape science and philosophy, postmodernity should also be mentioned, especially Foucault. Now, in 2025, my opinion is that the debate about postmodernity is not so important. What really matters is the future of AI: it is a jump from post-humanism to trans-humanism, Cyborg Revolution.

While the debate about postmodernity is basically academic, the debate about how to merge globalization, AI, and the Cyborg Revolution will have a huge impact on the future. Basically, the future is not an academic debate at Oxford or Cambridge; the future is being designed in AI labs at the very top level—or rather, at a classified level—not in academia anymore. At this level of intelligence, we can only publish what is publishable, which is just a minimum part of our work.]

42.9. The Ongoing Relevance of the Debate in Contemporary Science

Today, within the sciences, one still finds strong defenders of an **ideal of a neutral science**, free from any political or ideological entanglement. At the same time, however, there are also numerous scholars and philosophers who insist that science is always **politically and ideologically conditioned**.

This coexistence of positions reflects a persistent tension in contemporary epistemology. On one side, institutions such as physics, mathematics, and certain branches of biomedical research continue to hold up neutrality as a professional and methodological standard, arguing that their validity depends on **independence from external agendas**. On the other side, fields such as sociology, anthropology, and science and technology studies [AI, Cyborg Robotics] highlight the **social situatedness** of scientific practice, emphasizing the embeddedness of inquiry in structures of funding, governance, and ideology. Thus, the neutrality/politicity debate remains **alive and unresolved**, not only within philosophy of science but also in the day-to-day practice of research.

42.10. Contemporary Paradigms and the Persistence of Positivism

It is sufficient to open contemporary textbooks in virtually any scientific discipline to discover a great diversity of schools, each with its own position on the political or ideological role of science. Yet, despite this plurality, the **fundamental paradigms remain in force**. Postmodern theory has long proclaimed the arrival of a new era in which positivism, rationalism, and materialism have been consigned to oblivion. In reality, however—and contrary to postmodern claims—numerous contemporary scientists of high prestige still identify themselves as **positivists or rationalists**.

A telling example is **Stephen Hawking**, who in various publications explicitly described himself as a positivist, even while contributing to some of the most advanced areas of theoretical physics, such as the understanding of black holes and the role of the Higgs

boson in particle physics. This shows that **positivism is not merely a historical relic** but a living paradigm, still claimed as an intellectual identity by leading figures in science.

What we see, therefore, is not the disappearance of modern paradigms, but their **reconfiguration** within plural scientific contexts. Rationalism persists in the reliance on mathematical formalization, positivism in the empirical testing of hypotheses, and materialism in the recognition of natural and social constraints. The persistence of these paradigms underscores that **postmodern relativism has not replaced the foundations of scientific practice**, even if it has sharpened awareness of their limits.

42.11. Influences in *Impossible Probability*

Readers who have already encountered *Introduction to Impossible Probability: The Statistics of Probability or Statistical Probability* will have noticed that this theory is an **amalgam or synthesis** of diverse philosophical influences. It explicitly reveals the marks of **positivism, critical rationalism, and dialectical materialism**.

Impossible Probability does not attempt to choose definitively between neutrality and politicization, nor between empiricism and rationalism. Instead, it develops a **synthetic framework** that acknowledges the strengths of each tradition: ***from positivism, the commitment to methodological rigor; from critical rationalism, the principle of falsifiability and rational critique; and from dialectical materialism, the recognition of science's ideological and political situatedness.*** This synthesis positions Impossible Probability as a **unique contribution** to the philosophy of science, capable of integrating divergent traditions into a coherent methodological paradigm.

42.12. Dialectical Synthesis with a Margin of Error

As explained in other sections, Impossible Probability arrives at a **synthesis of otherwise contradictory schools of thought**. This synthesis is made possible through a principle derived from **Hegelian dialectics**, namely that **opposites are identical**. Yet

in Impossible Probability, this principle is reformulated: the identity of opposites holds only **within the acceptance of a margin of error** in propositions.

Thus, rationally accepted hypotheses are recognized as provisionally valid, but always subject to potential rejection in the long run, either because of new empirical findings or the passage of sufficient time. In this framework, the dialectical identity of opposites becomes a **critical rational identity**, conditioned by the limits of knowledge and the inevitability of error.

This means that even the contradiction between neutrality and politicization can be synthesized, but not by eliminating the contradiction. Rather, the synthesis occurs in the recognition that both positions are valid **within limits defined by error tolerance**. Neutrality can function as an ideal, but only provisionally; politicization is inevitable, but also bounded by the corrective mechanisms of scientific method. In this way, Impossible Probability makes dialectics **operational** in the philosophy of science.

42.13. A Unified Method for the Empirical Sciences

Impossible Probability arrives at its synthesis regarding scientific policy by affirming that all **empirical sciences—natural or social—must be studied using the same method**, namely the **hypothetico-deductive method**. In this respect, the theory reveals its **positivist lineage**, as positivism traditionally defended the unity of scientific method across domains.

The insistence on a single method stems from the conviction that **empirical verification and deductive rigor** are the only means to secure reliability in science. This also implies a critique of the traditional division between social and natural sciences, which Impossible Probability considers outdated. Instead, it calls for a classification of sciences more in line with **Kantian critical rationalism**: not based on their subject matter (society vs. nature) but on the **structure of their reasoning and methods**.

42.14. Critique of the Social/Natural Division

The traditional division between the social sciences and the natural sciences, according to Impossible Probability, is no longer adequate. All such sciences are, in essence, **empirical sciences** and should be studied using the same hypothetico-deductive method. The more meaningful distinction, it argues, is between **synthetic sciences** and **analytic sciences**.

- The **synthetic sciences** encompass both the natural and social sciences; they are empirical and aimed at explaining phenomena through the testing of hypotheses.
- The **analytic sciences**, by contrast, include logic, mathematics, and philology or linguistics; they do not study empirical phenomena directly but provide the formal and linguistic tools necessary for scientific reasoning.

This reframing aligns with a broader philosophical movement to **rethink epistemological boundaries**. Instead of reinforcing disciplinary divisions based on objects of study, it focuses on the **mode of inquiry** and the type of propositions advanced. Synthetic sciences produce empirically testable claims; analytic sciences clarify the formal conditions of such claims. In this way, Impossible Probability situates itself at the crossroads of positivism and critical rationalism, offering a more **systematic classification of scientific knowledge**.

42.15. A New Distinction: Synthetic vs. Analytic Sciences

Once the traditional division between social sciences and natural sciences is overcome—since both are subsumed under the broader category of **empirical sciences**, equally governed by the **hypothetico-deductive method**—a more fundamental distinction emerges. The genuine differentiation, according to *Impossible Probability*, lies between **synthetic sciences** and **analytic sciences**. The former comprise all empirical disciplines, while the latter encompass the study of logic and

languages: the **mathematical language of science** and the **linguistic analysis of spoken and written languages**,[in fact this is neo-positivism].

This reclassification follows a **Kantian rational-critical line**, which emphasizes the form of knowledge rather than the object studied. Synthetic sciences generate knowledge by synthesizing empirical data with hypotheses; they are productive of content about the world. Analytic sciences, by contrast, clarify, formalize, and regulate the languages and logical structures through which scientific claims are articulated. In this way, the analytic disciplines serve as the **formal scaffolding** of all scientific practice, while the synthetic disciplines provide the **empirical content**.

42.16. Positivist Conclusion and Kantian Distinction

In this sense, *Impossible Probability* arrives at a conclusion that resonates with **positivism**: it overcomes the contradiction between the social and natural sciences by affirming that both must be studied using the same **scientific method**, the hypothetico-deductive method. At the same time, it advances a **Kantian-inspired, rational-critical distinction** between the sciences: dividing them into **synthetic sciences** (empirical sciences) and **analytic sciences** (logic and languages, whether mathematical or linguistic).

This dual alignment shows how *Impossible Probability* **bridges traditions**. From positivism, it takes the conviction that all empirical sciences share a common method. From Kant, it inherits the insight that distinctions between sciences are not merely empirical but **epistemological and methodological**. Thus, rather than preserving artificial separations (e.g., society vs. nature), it organizes scientific knowledge by the **kind of reasoning employed**—empirical synthesis versus analytic deduction.

42.17. Particular Methods of Rational Criticism

Within this classification, one can already perceive a **synthesis between positivism and critical rationalism**. For the **synthetic sciences**—that is, the empirical sciences, whether social or natural—the general method remains hypothetico-deductive. Yet, within this framework, there exist **particular methods for rational criticism**, which in fact function as sets of techniques for contrasting data. These include:

- the **Impact of Defect**,
- the **Second Method**,
- the **Effective Distribution**,

along with other models of data-contrast techniques and rational criticism explored throughout *Impossible Probability*. For example, ranking models, or methods that directly use **raw frequencies and direct scores**, are incorporated as tools of empirical critique.

Here the theory shows its **practical breadth**: rational criticism is not abstract but instantiated in concrete statistical methods. By systematizing diverse techniques under its framework, *Impossible Probability* provides both a **meta-theoretical synthesis** (positivist + critical rationalist) and a **methodological arsenal** for empirical research.

[The synthesis between positivism and critical rationalism in *Impossible Probability* is clear; the synthesis with dialectical materialism emerges as soon as we recognize the ideological role of politics in science and philosophy.]

42.18. The Syllogism of Tendency in Analytic Sciences

For the **analytic sciences**, and in particular for mathematics, *Impossible Probability* provides a different foundational tool: the **Syllogism of Tendency**, a deductive method applied to the theoretical development of probability statistics.

Whereas synthetic sciences operate empirically, analytic sciences operate **formally**. The Syllogism of Tendency is conceived as a way to establish **necessary connections** between statistical concepts, enabling the deduction of theoretical models that can later be tested in synthetic sciences. It is here that the **philosophical lineage of deductivism**—from Aristotle through Kant to contemporary rationalist traditions—enters directly into the statistical theory, grounding probability not only in experience but in logical necessity.

[If the range of any empirical probability is from zero to one, then the maximum possible empirical probability is one and the minimum possible empirical probability is zero. If the sum of all empirical probabilities is one, then the arithmetic mean is one divided by N, the inversion of N. Therefore, the Bias Level is the empirical probability minus the inversion of N, and the average of all Bias Levels is the Mean Deviation. Following this sequence of syllogisms applied to the tendency of probability, it is not difficult to arrive at the calculation of the Maximum Theoretical Mean Deviation and all the theoretical and empirical values developed by *Impossible Probability*; you only need to follow the sequence of syllogisms applied to the tendency of empirical probability.]

42.19. A Common Deductive Paradigm

If positivism is integrated into *Impossible Probability* by affirming a single methodology for all **synthetic sciences** (whether natural or social), and if at the same time the theory develops a **critical rational vision** of science that distinguishes synthetic from analytic sciences, the next step is more radical: even this distinction is ultimately **overcome**.

In general, all sciences—whether synthetic or analytic, empirical or non-empirical—are founded upon **logical deduction**, the core principle of both idealist and rationalist

theories of science. Synthetic sciences are grounded in the hypothetico-deductive method; analytic sciences in the purely deductive method. Thus, **all sciences are, in essence, deductive**. Consequently, the true paradigm of science, in *Impossible Probability*, must be the **deductive paradigm**, aligned with the traditions of idealism and rationalism.

This conclusion transforms the debate. Neutrality vs. politicization, empiricism vs. rationalism, natural vs. social—these oppositions dissolve into a **unified paradigm of deduction**. Deduction is not opposed to empiricism but **structures it**, by providing the logical architecture that gives meaning to empirical findings. Therefore, *Impossible Probability* does not merely add to the philosophy of science; it redefines it by situating **deduction as the universal framework of all scientific practice**.

42.20. Recognition of the Politicity of Synthetic Sciences

At the same time that *Impossible Probability* produces its synthesis between positivism and critical rationalism—and thereby also integrates idealism and rationalism in the defense of the **deductive paradigm** in science—it acknowledges that, within the **synthetic sciences** (whether empirical social or natural sciences), there exists an unavoidable **ideological or political reality of science**. Science, insofar as it is a **human product**, is inherently political and ideological. Following Aristotle's definition of the human being as a *zoon politikon* (political animal), every human product inevitably reflects its **political condition**.

This recognition is not a contradiction of scientific rationality but a complement to it. Even while insisting on the deductive and methodological unity of science, *Impossible Probability* accepts that knowledge is always embedded in human contexts. Every scientific statement, no matter how rigorously derived, is also a **social act**: it is generated by political beings, funded by political institutions, and deployed within political frameworks. Thus, science's political dimension is not accidental but **constitutive of its existence as a human practice**.

[What is important to highlight about the importance of Marx and Engels in relation to Aristotle is the fact that Aristotle recognized the political human condition. However, in ancient times the notion of ideology was not clear. We can say that what we now call ideology was then shaped by myths and religion, but even this analogy is not enough to represent the value of ideology today. Even though materialists like Aristotle recognized the political value of philosophy and science from the outset, it was not until Marx and Engels began their work that the concept of ideology started to be seriously analyzed in science and philosophy. Auschwitz was not only politics; Auschwitz was ideology. The work of Mengele was an ideological construction of science. While the scientific work of Mengele was lost, confiscated, or reclassified, the only vivid memory of that scientific horror is the testimony of its survivors.]

42.21. Science and Politics: A Practical Dialectic

If, since Aristotelian empiricism, the human condition has been understood as essentially political, and if from the nineteenth century onward the **critical theses of dialectical materialism** reinforced this view, then the political and ideological function of science becomes undeniable. Indeed, science itself can become a **political directive**, in the sense that:

1. **Scientific claims are subject to politics**—their funding, dissemination, and interpretation are influenced by political agendas.
2. **Politics is subject to science**—policy decisions, laws, and collective goals are often justified and structured on the basis of scientific knowledge.

This creates a **dialectical relationship**: science influences politics, and politics influences science. Neither can be fully understood in isolation from the other.

This dialectic is visible in diverse historical episodes: the role of Newtonian mechanics in shaping Enlightenment politics, the use of Darwinian theory in ideological disputes about social order, or the reliance on climate science in contemporary environmental policy. In each case, scientific knowledge and political projects are **mutually**

constitutive. *Impossible Probability* frames this not as contamination of science, but as the **practical reality** of how knowledge and power interact.

42.22. Institutional Scientific Policy

In today's world, the **political function of science** is made concrete in institutional practices. In both private and public enterprises that maintain research and development departments, in universities that manage projects of scientific inquiry, and in *governments that allocate budgetary resources*, decisions about science are always conditioned by **political priorities**.

The choice of which projects receive funding, which lines of research are incentivized, and which orientations prevail in scientific development is never neutral. It depends on the **scientific policy of the sponsoring or patron institution**. This policy determines whether one project is supported over another, whether one direction of inquiry flourishes while another is stifled.

Scientific policy thus becomes a decisive **mediating framework** between scientific autonomy and social demands. **It selects, prioritizes, and channels scientific activity** in accordance with broader ideological and political objectives. Far from being incidental, institutional policy is the **structural condition of possibility** for contemporary science.

42.23. The Scope of the Role of Scientific Policy

The role of scientific policy today is indisputable. Moreover, its function extends far beyond that of a mere **advisor, inspector, or sanctioning authority**. Scientific policy does not merely oversee research to ensure that it remains aligned with the ideological and political principles of the sponsoring institution. Rather, its role is much broader: it **shapes the very orientation of scientific research**.

From the perspective of the philosophy of science, scientific policy is not only regulatory but **constitutive**. By determining which projects are pursued, it decides

which questions can be asked and which answers are possible. Scientific policy therefore acts as a **meta-methodological condition**: it defines the space within which scientific rationality operates. The inspector function (ensuring compliance) is secondary compared to the **directive function** (establishing priorities and limits).

42.24. Empirical and Political Premises in Hypotheses

In *Impossible Probability*, the synthetic sciences employ the **hypothetico-deductive method**, as explained in Section 10 of *Introduction to Impossible Probability*. Within this framework, the premises upon which conclusions are built are not exclusively empirical. For example: if the percentage of A over B is X, and the percentage of B over C is Y, then the percentage of A over C is Z. Such premises are strictly empirical.

However, in addition to empirical premises, there are also **ideological or political premises** upon which empirical hypotheses are constructed and subsequently subjected to rational criticism.

This claim is crucial: hypotheses are not only shaped by data but also by **the values and political assumptions that frame which hypotheses are considered relevant, how variables are defined, and what counts as valid evidence**. In this sense, even when applying rigorous methods of statistical probability, scientific practice cannot be abstracted from its **political context of formulation**. The recognition of these dual premises—empirical and political—constitutes one of the defining innovations of *Impossible Probability*.

42.25. The Empirical Nature of the Hypothesis

In *Impossible Probability*, the **empirical character of a hypothesis** derives from the fact that every hypothesis is the empirical product of the **physiological processes of the brain** in its elaboration. That is to say, the hypothesis is not empirical because it corresponds to some external empirical element independent of the subject; rather, its empirical nature stems from the fact that its very **generation is a physiological process** occurring within the brain. In this process, the brain's physiological machinery is ***activated*** to produce hypotheses.

For this reason, the hypothesis is considered empirical: in essence, every hypothesis is an **idea that seeks to reflect reality**. The central aim of the method of rational criticism is to test whether the idea produced by the brain is **isomorphic to reality**—whether it mirrors it sufficiently. This pursuit of isomorphism is precisely another point of convergence between *Impossible Probability* and the tradition of **positivism**.

This reframing shifts the discussion: empirical status does not belong exclusively to external data but also to the **internal cognitive act of hypothesis formation**. Thus, the very act of thinking scientifically is already empirical, since it is the product of embodied, physiological processes. Science, therefore, is empirical not only in its objects but in its **subjective genesis**.

42.26. Isomorphism Within a Margin of Error

However, this idea—empirically produced by the brain's physiology—only achieves **isomorphism with reality within a margin of error**. The extent of this margin is not given a priori but is **decided by scientific policy**.

Expanded context. This means that no hypothesis can ever claim perfect correspondence to reality. Instead, hypotheses are evaluated according to thresholds of acceptability: how much deviation from reality is tolerable before a hypothesis is rejected. This introduces a **normative dimension** into science: defining the acceptable error margin is both a methodological and a political act. Hence, isomorphism is never absolute but always **conditional upon the conventions of scientific policy**.

42.27. Functions of Scientific Policy

Scientific policy thus fulfills multiple functions:

1. **Project selection.** Given a set $N$of possible scientific projects and the impossibility of developing all of them simultaneously, scientific policy determines their ***order of priority***. This prioritization already reflects political and ideological choices.

2. **Hypothesis formulation.** Scientific policy plays a role in the elaboration of empirical hypotheses, insofar as these hypotheses synthesize both empirical data and **ideological–political premises**.
3. **Error determination.** Scientific policy decides the acceptable **level of error**—whether empirical error (error de hecho) or rational error (error racional). This includes the choice of **models of rational criticism** and **techniques of hypothesis testing** to be used in evaluating empirical hypotheses.

In this way, scientific policy is not external to science but **constitutive of its *internal operations***. It determines which questions are ***investigated***, how hypotheses are framed, and what standards of validity are applied. Thus, scientific policy is a **meta-epistemological framework**, shaping both the direction and the evaluation of scientific activity.

42.28. Acceptance of Empirical Error

The acceptance of **empirical error** entails acknowledging that a science without error is impossible, thereby dismantling the positivist ideal of a purely neutral science. It is humanly impossible to construct a science without error: the moment the **human factor** enters the scientific process, error becomes inherent.

The reason for this inevitability is that, given the **infinity of variables affecting reality**, it is impossible to attain absolute objectivity. Modern science cannot measure everything that occurs; it can only measure a portion, and that portion constitutes a **sample**. By accepting that error is inversely proportional to the size of the sample, science acknowledges that it can reach only **levels of veracity**—degrees of truth or political reality—rather than an unattainable absolute truth. This is the contradiction between the **finite human being** and the potentially **infinite universe of singular particulars**.

Empirical error is not a defect to be eliminated but a **structural condition** of knowledge. Every act of measurement implies exclusion, every sample implies limitation, and every conclusion is subject to revision. Thus, the presence of error marks both the **fragility**

and the **progressive dynamism** of science. Rather than undermining scientific validity, the recognition of error situates science within its **proper horizon: provisional, finite, and self-correcting**.

[One of the reasons to design GAI is the possibility of achieving levels of reasoning far beyond human science, as well as the possibility of eliminating rational error. Even though the error attached to the sample is unavoidable—though reducible—as long as GAI can work with increasingly larger samples, it can reduce the error linked to sampling, even if it cannot be fully eliminated as long as samples are required. Here is the key point: the goal is not to build GAI to eliminate all kinds of error, but to train GAI to reduce rational error gradually, to the point where it could eventually be eliminated, while at the same time working on how to scale the magnitude of the samples in order to reduce the representativeness error of sampling]

42.29. Sampling and the Error of Representativeness

The acceptance of **empirical error** also entails accepting that without samples of data or scientific evidence, science would not be possible. In universes of subjects or options conceived as infinite, it is impossible to study **all subjects or all options**. Even in a universe that is not strictly infinite but sufficiently vast to exceed the limits of exhaustive knowledge, the impossibility of encompassing all subjects or options forces researchers to select a **sample**.

Similarly, in universes of limited options where the number of direct scores or frequencies can still be indefinitely large, the necessity of working with a sample already constitutes an admission of empirical error: the **error of representativeness**.

This error is formally expressed as the **inverse of the sample**:

- In universes of infinite subjects or options:

$$\frac{1}{N}$$

where $N$is the sample of subjects or options.

- In populations, the error corresponds to accepting a **particular population at a particular moment in time**—and only that one—despite the fact that it may not be absolutely representative of the entirety of history. [In that case N is the number of subjects or objects in that population.]
- In universes of limited options:

$$\frac{1}{\Sigma x_i}$$

- where Σx_irepresents the sum of direct scores or frequencies.

In short, sampling is both the condition of possibility for empirical science and the origin of its inherent limitation. To study is to select; and to select is to exclude. Therefore, science's capacity to describe and predict reality is inseparable from its necessary acceptance of **representational incompleteness**.

42.30. Acceptance of Rational Error

In addition to empirical error, scientific policy must accept a margin of **rational error**, which arises from the method of rational criticism chosen—specifically, the technique of hypothesis testing. This is expressed in terms of a **critical ratio**, which corresponds

to a percentage X (error or reliability) out of 100, applied against an ideal or maximum trend.

- If interpreted as **error**, the percentage X indicates the maximum margin of error within which a hypothesis may still be accepted as provisionally valid, possibly only for a finite period or even for an indefinitely long time.
- If interpreted as **reliability**, the percentage X implies an associated error margin equivalent to 100 – X.

Rational error is the price of methodological decision. Each test—whether significance testing, confidence intervals, or more complex inferential models—implicitly accepts a level of uncertainty. Rational criticism therefore introduces a **normative threshold** for decision-making: beyond a certain probability of error, hypotheses are rejected, not because they are logically impossible, but because they are judged scientifically **inadmissible** within the adopted standards.

42.31. Zero Rational Error and the Persistence of Empirical Error

Even if scientific policy were to impose the most **demanding threshold**, requiring 100% reliability and 0% error in the critical ratio X—that is, demanding zero rational error in the model of hypothesis testing or rational criticism—**empirical error would still remain**.

In other words, even if rational error were theoretically eliminated, the **error of representativeness inherent to sampling** would persist. For this reason, scientific policy must always accept the existence of **possible error** in its investigations—whether empirical or rational.

This conclusion underscores the impossibility of an absolutely error-free science. Rational techniques can be tightened, thresholds can be raised, and criteria can be formalized; but the fact remains that **no sample is the universe itself**. Thus, the claim to perfect neutrality or absolute truth collapses in the face of representational limits.

42.32. Empirical Skepticism and Falsification Over Time

Once scientific policy accepts a margin of error, this margin transforms into a space of **empirical skepticism or rational doubt**. Every empirically accepted hypothesis, even when rationally sanctioned as provisionally valid, remains subject to doubt.

As long as the possibility of error exists, in a sufficiently long—or even infinite—timeframe, it becomes **inevitable** that the hypothesis may eventually be shown false. This occurs when a previously unobserved event—excluded from the sample—takes place in the universe. Such an event, by definition within the accepted margin of error, may appear "impossible" but can in fact be **unavoidable**.

This perspective brings *Impossible Probability* into dialogue with both **empiricist skepticism** (e.g., Hume's insistence that causal relations are habits, not necessities) and **critical rationalism** (Popper's emphasis on falsification). It asserts that science's strength does not lie in claiming final truth, but in **remaining permanently open to revision**. Error is not a flaw but the very mechanism that ensures the dynamism of scientific knowledge, embedding it within a continuous process of **hypothesis, doubt, and potential refutation**.

42.33. Synthesis: Hume, Descartes, and Critical Reason

When the margin of error is defined as a margin of **empirical skepticism or rational doubt**, philosophy is once again brought into synthesis. On the one hand, there is **Humean skepticism**, according to which every causal relation is a mere habit of thought, never guaranteed to hold universally, and therefore always open to future refutation. On the other hand, there is **classical Cartesian rationalism**, which holds that the true motor of science is **rational doubt**: nothing is to be accepted uncritically, and every claim must remain perpetually subject to the scrutiny of reason.

From Kant onward, the synthesis of these two traditions produces what is called **critical reason**. In *Impossible Probability*, this synthesis is made explicit: science advances neither by blind empiricism nor by rigid rationalism, but by the **interplay**

between skepticism and rational criticism, held together within an explicit margin of error.

This framing situates *Impossible Probability* firmly within the philosophical lineage that connects empiricism, rationalism, and their Kantian unification. It shows that science's vitality depends not on certainty but on its **capacity for self-doubt and provisionality**, elevated into a methodological principle.

42.34. Error as a Moral Variable

The margin of error—whether empirical or rational—is also subject to **scientific policy**, which adds yet another function to the latter: to guarantee the **moral representativeness** of scientific results.

The less error scientific policy is willing to tolerate, the greater the **moral guarantee of rational truth** in the accepted hypothesis. Conversely, the greater the margin of error tolerated, the more **politically immoral** science becomes. In this sense, the percentage of error X in rational criticism becomes a **moral variable**, guaranteeing or undermining the moral presumption of the results.

This logic applies both to rational error margins in hypothesis testing and to the **error of representativeness in sampling**, as already outlined in *Introduction to Impossible Probability*.

Thus, *the question of error is not only epistemological but* ***ethical and political***. Accepting too much error dilutes the moral authority of science, while stricter criteria provide stronger assurances of responsibility. Error margins become **ethical thresholds**, linking scientific truth to political accountability.

42.35. Provisionality and the Limits of the Universal Imperative

At its core, *Impossible Probability* asserts that as long as science is **provisional**, it cannot achieve the Kantian **first moral imperative** of universal validity. Science is

universally provisional, not universally absolute in the sense of the categorical imperative.

Science can only be **as moral as possible**, within its acknowledged margins of error—empirical or rational—while striving toward ever greater **isomorphism between science and reality**. Yet, in the long run, science will never attain final truth. It will remain an endless sequence of provisional hypotheses, each eventually refuted, only to be replaced by hypotheses that are **truer, less erroneous, but never error-free**.

This perpetual process of falsification and substitution generates the **spiral of scientific revolutions**, propelling progress toward truth that is always "less partial" but never complete. Doubt and skepticism remain permanent companions of science. As long as science involves human factors, it will remain subject to error, and thus always accompanied by **empirical skepticism and rational doubt**, the very essence of **critical reason**.

This vision aligns with both **Popper's falsificationism** and **Kuhn's theory of scientific revolutions**, but reframes them in Kantian and moral terms: science progresses not toward certainty but toward **increasingly refined provisional truths**, morally bound by their explicit acceptance of error.

42.36. A Political Definition of Science in *Impossible Probability*

For all these reasons, *Impossible Probability* defines science in **political terms**. Scientific policy determines the **criteria of priority** in the selection of research projects: discarding those not aligned with its framework and developing those that are.

Scientific policy plays an essential role in the **formulation of hypotheses**, which are framed within the ideological parameters of the prevailing political context. At the same time, it governs the **acceptance of error margins**, both empirical and rational, and thus decides whether a given empirical hypothesis will be accepted or rejected.

In essence, every statistical decision is a **decision of scientific policy**. Far from being an external influence on science, policy is **embedded within its very logic**, shaping the questions asked, the methods employed, and the conclusions accepted. By making

this explicit, *Impossible Probability* situates itself as both a philosophy of science and a philosophy of politics, uniting them in the recognition that science is never outside ideology, but rather its most structured and rational form of expression.

Rubén García Pedraza, Madrid 19 de diciembre del 201[2]

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43. Science

43.1. Defining Science and Its Core Purpose

Science, in its broadest sense, can be understood as any systematic endeavor whose objective is to achieve **reliable knowledge of reality**. While there exist multiple definitions of science shaped by different philosophical, scientific, and political paradigms, the most widely accepted view is that science aims to provide the **most objective form of knowledge possible**.

Nevertheless, this apparently unifying definition conceals deep debates. A central question is whether scientific knowledge, unlike other forms of knowledge, should remain entirely **free of ideological or political variables**. From a **positivist perspective**, science is conceived as *neutral knowledge*, detached from politics and ideology. From alternative perspectives, however, the **political role of science** is highlighted and made explicit. For this reason, within *Impossible Probability*, special emphasis is placed on the inescapable role of **scientific policy** as an integral part of the scientific enterprise.

43.2. Science in the General and Particular Senses

When discussing science, it is necessary to distinguish between:

1. **Science in the general sense**—an abstract noun encompassing all conceptions, methods, and systems of knowledge collectively.
2. **Particular sciences**—specific disciplines that develop their own objects of study, theories, and methodologies.

Science in the general sense tends to be governed by a **dominant paradigm**, which provides stability for a time. However, when the paradigm enters into crisis, a

paradigmatic crisis emerges. Unless a **paradigmatic revolution** occurs, science may remain in a state of **permanent crisis**, unable to reorganize itself into a new stable framework.

43.3. Cycles of Paradigmatic Crisis and Revolution

Just as general science is vulnerable to crises, so too are the **particular sciences**, each of which may depend on its own paradigms. These paradigms can likewise enter into crisis, producing cycles of:

- **paradigmatic crisis**,
- **paradigmatic revolutions**, and
- new **stationary periods of stability**.

Over time, such cycles recur in both general science and the particular sciences, creating a rhythm of crisis, revolution, and re-stabilization. Ultimately, this cyclical process tends toward the prospect of a **stationary state of permanent scientific revolution**, where science is continually transformed rather than resting in long-term stability.

This framework resonates with Thomas Kuhn's analysis of paradigm shifts but reinterprets it through *Impossible Probability* as a **structural feature of science itself**, rather than an occasional disruption.

43.4. Rethinking the Traditional Distinction

Traditionally, science has been divided into **social sciences** and **natural sciences**. In *Impossible Probability*, however, this distinction is regarded as **inadequate**. Both social and natural sciences are equally grounded in **positive facts**, and therefore both must be held to the same standard of **objectivity**.

Accordingly, *Impossible Probability* proposes a different classification: the more appropriate distinction is between **synthetic sciences** and **analytic sciences**.

- **Synthetic sciences** (also referred to as **empirical disciplines**) encompass both natural and social sciences, united by their empirical engagement with reality.
- **Analytic sciences** include disciplines such as logic, mathematics, and linguistics, which focus on the analysis of formal structures and languages rather than empirical data.

43.5. Structure of Science in *Impossible Probability*

In general terms, whether we are dealing with science as a whole or with particular synthetic sciences, *Impossible Probability* describes their structure as follows:

1. **Empirical hypotheses** are subjected to rational criticism under the margin of error accepted by scientific policy.
2. Rational criticism determines whether a hypothesis has **sufficient rational validity**.
3. If judged sufficiently rational, the hypothesis is accepted provisionally and incorporated into the body of a particular science.
4. A set of empirical hypotheses constitutes a **scientific theory**.
5. A set of theories constitutes a **scientific model**.
6. A model, or a collection of models, may aspire to the status of a **scientific paradigm**.

Thus, the development of science is portrayed as a **hierarchical progression**: hypotheses → theories → models → paradigms. The struggle to establish a new paradigm—whether in a particular discipline or in science as a whole—is the very process that drives **scientific advancement**.

This schema underscores the inherently **provisional** nature of scientific knowledge, while simultaneously situating it within a process of constant **paradigmatic competition**. Science is not static but an evolving field shaped by rational criticism, empirical testing, and the contest for paradigmatic authority.

[he construction of science in this context is not very different from GAI. Empirical science is related to the factual hemisphere of the brain and to rational truth for building models and projects, which will ultimately merge with the Global Project System (GPS). Language understood as categories to read the external world, on the other hand, is related to the categorical hemisphere of the brain, responsible for the construction of conceptual models, schemes, and projects. At the same time, mathematics and logic, as analytical disciplines, represent Real Intelligence. Under investigation through the Learning System and Artificial Engineering, it may become possible to develop a non-human mathematical language, and therefore mathematical operations beyond human mathematics. Our view is that at some point AI will develop non-human pure operations.]

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44. Synthetic Sciences

44.1. Defining the Synthetic Sciences

Synthetic sciences are defined as those disciplines that begin with the study of **positive facts expressed in the form of empirical data**. Within this category fall both the **natural sciences** and the **social sciences**, which are equally considered synthetic sciences.

The key unifying feature is that both types of sciences require the **collection of empirical evidence** as the foundation for applying reliable methods of study. In the framework of *Impossible Probability*, this entails the application of **statistical probability**—both for the construction of empirical models (based on descriptive data) and for the testing of hypotheses or predictions, whether along **projective trends** (forward projections) or **prognostic models** (predictive forecasting).

Expanded context. This definition challenges the traditional division that treats natural and social sciences as essentially distinct. Instead, it asserts their fundamental methodological equivalence: both are synthetic because both are grounded in data that must be subjected to rational and statistical scrutiny.

44.2. The Social Sciences as Synthetic Sciences

The social sciences encompass all empirical disciplines that focus on **human behavior**, whether individual or collective. These sciences require the collection of data either from **samples** or **populations** of human subjects in order to:

1. **Describe** behavioral patterns, whether in historical or contemporary contexts.
2. **Test hypotheses** that explain social tendencies, dynamics, or structures.

3. **Apply technology** to human groups, measuring its effects empirically and rationally.

In *Impossible Probability*, the social sciences gain methodological legitimacy by being treated on the same plane as natural sciences. They are not "softer" sciences but are equally synthetic in that they rely on **empirical observation, statistical modeling, and rational critique**.

44.3. The Natural Sciences as Synthetic Sciences

The natural sciences, in turn, comprise all empirical disciplines that study the **behavior of matter**. Like the social sciences, they require the collection of empirical data, but their focus is on physical, chemical, biological, and material processes. These data serve as the basis for:

- the construction of **descriptive models** (capturing what is observed), and
- the formulation of **predictive models** (explaining or anticipating behavior through hypotheses or technological applications).

Within *Impossible Probability*, natural sciences are not granted methodological superiority over the social sciences. Both are subjected to the same scientific logic, where data are the foundation, and **statistical probability** provides the main instrument for explanation and prediction.

44.4. The General Synthetic Method

In *Impossible Probability*, the **general method** that applies to all synthetic sciences is the **hypothetico-deductive method**, commonly referred to as the **scientific method**. This method involves:

1. the formulation of hypotheses,
2. the deduction of consequences from those hypotheses, and
3. their empirical testing against observed data.

Because this general method governs both natural and social sciences alike, *Impossible Probability* emphasizes the unity of the scientific enterprise.

The hypothetico-deductive method is considered synthetic in this framework because it integrates empirical observation with deductive reasoning, binding the two into a single systematic approach to scientific inquiry.

44.5. Specific Methods in *Impossible Probability*

Alongside the general scientific method, *Impossible Probability* proposes a set of **more specific methods** tailored for empirical sciences. These include:

- **The Impact of the Defect** – a method for identifying and measuring deviations or errors in data.
- **The Second Method** – a systematic framework for rational criticism based on statistical probability.
- **Effective Distribution** – a method for analyzing the spread and allocation of empirical phenomena.
- **Ranking studies** – techniques for ordering and comparing empirical entities within a sample.
- **Direct application of rational criticism models** – using the Second Method applied directly to raw scores or frequencies.

These methods are presented not as alternatives but as **extensions** of the hypothetico-deductive framework. They operationalize the general logic of science into concrete statistical and rational techniques, making it possible to apply scientific reasoning to both **descriptive and predictive contexts** across the full range of synthetic sciences.

[The very concept of synthetic science highlights how Artificial Research by Deduction works: as a synthesis of empirical data and mathematical equations, the synthesis of data and reason, the synthesis of the external world with internal pure reason. That is why it is synthetic knowledge. Artificial Research by Application is also synthetic

knowledge, but in a different way. Instead of making deductions, Artificial Research reads/interprets the world through the application of categories as a language.]

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45. Analytic Sciences

45.1. Defining the Analytic Sciences

Analytic sciences are those disciplines that, while requiring the **highest possible degree of reliability**, do not base their inquiries on **empirical data** or **positive facts**. Instead, they are devoted to the establishment of **formal relations** among abstract entities. For this reason, analytic sciences are also often referred to as **formal sciences**, in order to differentiate them from the **empirical sciences** (whether natural or social).

Within this category, we find **logic, mathematics, and linguistics or philology**. These disciplines exemplify the analytic sciences because their work is not grounded in empirical observation but rather in the study of **formal systems of relations**. For example, grammar, semantics, and morphology in linguistics do not rely on direct measurement of positive facts; instead, they concern themselves with the ways in which elements of a language relate formally to one another.

45.2. The Scientific Character of Analytic Sciences

Although analytic sciences do not derive their knowledge from empirical data, they are nonetheless **genuinely scientific**. Their scientific status rests on the **deductive nature of their reasoning**, through which they seek to achieve the highest possible degree of **objectivity in argumentation**.

- **Logic** formalizes the rules of valid reasoning.
- **Mathematics** develops structures, numbers, and relationships on the basis of axioms and deductive proofs.

- **Linguistics and philology** analyze the formal relations in human languages, such as grammatical structure or semantic systems.

In all these cases, the common denominator is not empirical measurement but **deductive consistency** and **formal rigor**.

Thus, analytic sciences are distinct from synthetic sciences, but no less rigorous. They reveal that the concept of science does not rest solely on empirical observation but can also be founded on the **systematic pursuit of formal truth** through deductive reasoning.

45.3. The Deductive Method in *Impossible Probability*

At the analytic level, *Impossible Probability* establishes the **deductive method** as its general framework. Deduction here means starting from **axioms or general principles or general definitions** and reasoning step by step toward specific conclusions whose validity depends on their logical derivation rather than empirical confirmation.

45.4. The Syllogism of the Tendency

Within this deductive framework, *Impossible Probability* introduces a specific methodological tool: the **Syllogism of the Tendency**. This is conceived as the **formal deductive foundation** for the development of the theory, providing a structured way of reasoning about probabilities, tendencies, and critical rational comparisons.

The Syllogism of the Tendency plays a role in analytic sciences similar to that of hypothesis testing in synthetic sciences. It does not require empirical data but provides the **formal structure** through which relations, trends, or proportions can be rationally deduced. It is, therefore, the cornerstone of the analytic dimension of *Impossible Probability*.

[In the construction of the Global Artificial Intelligence, Analytic Sciences play an important role in shaping the conceptual database within Artificial Research by Application. The way in which Application matches objects and categories is synthetic knowledge, but the inner structure of the categories, the list of categories, the taxonomy of categories—as concepts, as language—is analytical. In the same way, the inner structure of pure reason, as a collection of analytical categories, mathematical equations, belongs to the domain of Analytic Science. In the construction of conceptual sets, models, and maps, the analysis of categories and language once again becomes analytical: the analysis of sets of categories as language. At some point, the importance given by *Impossible Probability* to the definition of basic concepts, in order to later scale toward more complex structures such as GAI, reflects a clear neo-positivist influence.

In essence, mathematical, logical, or linguistic definitions by themselves are language—analytical knowledge. The study of analytical knowledge is the object of Analytic Science. When mathematical or logical definitions become operative, they function as methods; and as methods, when they are matched with empirical data, they produce synthetic knowledge. If the process is the matching of data and equations, it is Artificial Research by Deduction; if the process is the matching of categories and objects, it is Artificial Research by Application. On the other hand the analysis of relations between categories in categorical sets or maps could be define as well as analytical work or activity, although is not strictly analytical research itself.

While synthetic research is carried out by Artificial Research by Application and by Deduction, analytical research is performed by the Learning System when it needs to refine equations due to a high rate of errors in the attributional process, or by Artificial Engineering when researching how to improve the algorithms and the mathematical and logical processes of any AI or program]

This augmented translation is based on the post
published in https://probabilidadimposible.blogspot.com/,
On 29 December 2012.
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46. The Scientific Method

46.1. The Scientific Method as a Search for Reliability

The scientific method is the process through which knowledge is acquired in the most reliable way possible. Throughout the history of science, two broad paradigms have shaped debates concerning the scientific method. On one side, there have been philosophical traditions and scientific models that defend **inductivism, rooted in empiricism and materialism**, which emphasize the **accumulation of observations and their generalization into laws**. On the other side, there are traditions and models that defend **deductivism, especially within idealist and rationalist frameworks**, which give primacy to **logical reasoning and the derivation of conclusions from general principles.**

46.2. The Predominance of the Hypothetico–Deductive Method

The dominant view in modern science is that the scientific method takes the form of the **hypothetico–deductive** method. This is particularly applicable in the so-called **synthetic sciences,** which combine observation with experimentation and theoretical construction. By contrast, the **analytic sciences**, insofar as they do not rely directly on positive empirical facts, are fundamentally based on **logic**, which is by nature deductive. Therefore, broadly speaking, the method most widely recognized in both synthetic and analytic sciences is deductive reasoning.

46.3. Methodological Pluralism in the Sciences

Although deductive reasoning provides a general framework, its precise application depends on the particular branch of science: different disciplines require different

methodological adaptations. Hence, the choice of method varies depending on the nature of the science under study, giving rise to a plurality of methodological tools.

46.4. Deductive Methods in Analytic Sciences

Within **analytic sciences**, the deductive method of *Impossible Probability* is concretized in what is termed the **Syllogism of the Tendency**, which serves as its foundational logical structure. This logical instrument defines how reasoning processes are organized when empirical data are not directly available or when analysis is primarily conceptual.

46.5. Deductive and Hybrid Methods in Synthetic Sciences

In the synthetic sciences, the methodological approach is diversified into several particular methods, among which the most notable are the Impact of Defect, the Second Method, and the Effective Distribution. These methods combine empirical observation with ***rational models*** to achieve reliable knowledge, particularly when ***working with complex systems or probabilistic relations***.

46.6. Models of Rational Criticism

In addition, it is important to highlight the role of rational criticism models, which are applied in the form of ranking systems and as evaluative frameworks within the Second Method itself. These models serve not only to classify and compare but also to critique directly the empirical values of raw scores or frequencies, thereby enhancing both the ***descriptive and evaluative functions of statistical inquiry***.

[In GAI, the scientific method is clear: it is fundamentally **hypothetico–deductive**. Given a set of data, the question is what pure reason or category is most suitable for that collection of data. In **By Application**, deduction is still present, but it does not consist of matching pure reasons with data. Instead, it is the process of matching

categories, as language, with samples taken from things in the real world in order to determine what those things are. In short, **By Application** reads and comprehends reality, while **By Deduction** explains reality].

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On 29 December 2012,
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47. Omega models

47.1. Definition of Omega Models (Ω)

Omega models (Ω) are all those models in which, given a sample *N*, the magnitude of **ideal subjects or options is greater than one and less than *N***. In other words, within the total number of elements in the sample, there must exist a subset of ideal subjects or options whose size ranges between a minimum of two and a maximum of *N – 1*. For a model to be classified as "omega," there must therefore be at least two ideal subjects or options, while the upper limit is defined as the difference between *N* and one.

[All the subjects or options identified as ideals constitute the subset of omega subjects or options, denoted by the symbol omega (Ω). Therefore, omega (Ω) is equal to the number of subjects or options identified as ideals within N.

If in a omega model, omega, Ω, is a subset of ideals within N, as long as the theoretical probability for all N is the inversion of N, for the specific case of the ideals within omega, the ideal probability will be the inversion of omega, 1/ Ω= ideal probability]

This structure highlights that omega models operate between the extremes: unlike a scenario where there is only one ideal option (which would reduce to a singular ideal), or a scenario where all *N* options are ideal (equality), the omega framework functions in the intermediate space, where multiple but not all options can simultaneously be considered ideal.

47.2. Application to Multiple-Choice Testing

Consider the case of a multiple-choice test in which each item may have more than one correct answer. If the possible alternatives, correct answers, for a given item are represented by a sample *N* options, then the empirical probability of each option is

calculated as the direct score or frequency of that specific option divided by the sum of the direct scores or frequencies of all the options for that item.

When an item admits more than one correct response simultaneously, the ideal situation is that all the ideal options for that item—that is, all the correct answers—converge toward an empirical probability similar to the **ideal probability**, represented mathematically as the inversion of omega: **1/Ω**. By contrast, all non-ideal options—that is, incorrect or distractor answers—should converge toward the **Minimum Possible Empirical Probability**, which is zero.

This framework provides a rational way of evaluating the statistical behavior of multiple-choice questions with more than one correct answer, ensuring that the probabilities reflect not only the distribution of student responses but also the logical structure of correctness within the test itself.

47.3. The Omega Set as a Subset of N

The collection of all simultaneously ideal options within the same item is called the **omega set (Ω)**. This omega set is the subset of subjects or options that are truly ideal or correct within the larger set of *N* possible responses. In other words, out of all the alternatives available in the test item, only those belonging to the omega set are correct or ideal.

The omega set is thus always a **subset of N**, composed of two or more elements but fewer than the entire sample. It embodies the principle of multiple simultaneous idealities within a finite universe of possibilities, offering a structured way to distinguish correct responses from incorrect ones while preserving the logical consistency of the probabilistic model.

47.4. The Ideal Distribution of Probabilities within an Omega Subset

If we consider an omega subset (Ω) of ideal subjects or options within the total set N, the theoretically ideal condition would be that only the subjects or options classified as

***ideals* possess a non-zero empirical probability**. Conversely, for all the other, **non-ideal subjects or options, the ideal condition would be the Minimum Possible Empirical Probability**, that is, zero.

Thus, if for non-ideal elements the ideal empirical score or frequency is zero, then it follows logically that the total sum of all empirical scores or frequencies should be the result of distributing values exclusively among the subjects or options belonging to the omega subset. In cases where all the ideal subjects or options are considered equal in magnitude, and all non-ideal subjects or options are assigned a value of zero, the empirical probability for each ideal subject or option necessarily becomes equal to the inverse of the number of ideal elements in Ω.

Formally expressed, the empirical probability for any ideal subject or option within Ω is the inversion of omega:

$$p(x_i) = \frac{1}{\Omega}, x_i \in \Omega$$

This represents the **ideal probability**, given the existence of an omega subset within N.

47.5. Definition and Scope of Omega Models

Any model that includes, within the broader set N, a subset of ideal subjects or options (Ω), will be classified as an **omega model**. In the example previously discussed, the framework was illustrated by means of a test-like study, but the application of omega models is not limited to artificial or simplified testing situations. There are multiple real-world contexts where the presence of an identifiable subset of ideals within a larger set N would require the formal use of an omega model.

The principal defining characteristic of omega models is that they always include, within N, a quantity of ideals ranging between two and N minus one. This ensures that

the subset of ideals remains significant but does not collapse into trivial cases, such as when all or none of the elements are ideals.

47.6. Why Omega Models Require More than One Ideal

The main reason why omega models must contain at least two ideal subjects or options is that, if there were only a single ideal element, the model would no longer qualify as an omega model. In such a case, with only one ideal subject or option, the analysis would focus exclusively on the **positive bias** of that unique ideal element.

Indeed, if only one ideal exists within N, the empirical probability for that element would tend to approach the **Maximum Possible Empirical Probability**. Consequently, the **Level of Bias** would approach the maximum possible, whether considered in theoretical or empirical terms. In parallel, measures of dispersion, such as the **Mean Deviation** or the **Standard Deviation**, would also approach their maximum possible theoretical values.

Under these conditions, rational criticism could be carried out directly, at the **individual level**, by means of indicators such as the variance of the positive bias or the significance of positive bias. Likewise, other **critical proportions**—as explained in Section 11 of *Introduction to Impossible Probability: The Statistics of Probability or Statistical Probability*—would also become relevant tools of analysis.

At the **sample level**, the evaluation would be conducted through the **Critical Sample Level of Bias**, which, as detailed in the same referenced section, also includes measures such as the **Sample Significance of Positive Bias** and the **Critical Sample Proportions**.

47.7. The Case of Complete Equality of Ideals

If, in a given model, all subjects or options were equally ideal, then it would also not qualify as an omega model. If, for any N, all subjects or options that compose N are

equally ideal among themselves, then what we have is an **Equality of Opportunities Model**.

In such a model, the ideal condition is that the empirical probability of each subject or option should converge toward the **theoretical probability**, the **Level of Bias** should converge toward zero, and both the **Mean Deviation** and the **Standard Deviation** should converge toward zero sample dispersion.

Under these conditions, rational criticism would proceed through the use of **individual-level models**, such as the validity or significance of equality, as well as through **sample-level models**, such as the **Critical Sample Level of Equality**. Additionally, other critical proportions—either individual or sample-based—would apply. Some of these models have already been discussed in previous sections of the blog, while others are more extensively developed in *Introduction to Impossible Probability: The Statistics of Probability or Statistical Probability*.

47.8. The Position of Omega Models Between Extremes

Logically, if within a given N there is only one ideal subject or option, the ideal tendency is toward **maximum dispersion**, whether individual or sample-level. By contrast, if the entirety of N is equally ideal, then the ideal tendency is toward **zero dispersion**, again both individually and at the sample level.

Thus, those models that, within N, contain a number of ideals ranging from two to N minus one represent a **special type of model**. In these cases, because there is more than one ideal, the dispersion cannot tend toward maximum; and because not all of N is equally ideal, the dispersion cannot tend toward zero. Therefore, for **omega models**, the ideal dispersion is neither maximum nor minimum but rather a distinct condition: the **ideal dispersion**.

47.9. Measuring Dispersion in Omega Models

Dispersion at the **individual level** is measured through the **Level of Bias**, while dispersion at the **sample level** is measured through the **Mean Deviation** or the **Standard Deviation**. These indicators allow us to evaluate how far the empirical distribution deviates from its corresponding theoretical structure.

If, in an omega model, the ideal probability is the inversion of omega, $1/\Omega$, then the **ideal individual dispersion** will be equal to the **Ideal Level of Bias**, defined as the difference between the inversion of omega and the inversion of N:

$$\text{Ideal Level of Bias} = \frac{1}{\Omega} - \frac{1}{N}$$

47.10. Characteristics of the Ideal Level of Bias

The principal characteristic of the **Ideal Level of Bias** is that it must always be **positive**. However, it will never tend toward the **Maximum Theoretical Bias Possible**. This limitation exists because, as long as there is more than one ideal subject or option within N, the ideal probability can never be equal to the **Maximum Possible Empirical Probability**.

In summary, the **Ideal Level of Bias** establishes a structural measure of dispersion that is intrinsic to omega models. It ensures that these models maintain their distinctive position between the extremes of maximum and zero dispersion, providing a rational basis for critical evaluation.

47.11. From Ideal Probability to Ideal Dispersion

Once the **ideal probability** of an omega model is established, it becomes possible to calculate the **ideal individual dispersion**. As shown earlier, this is obtained from the difference between the inversion of omega and the inversion of N:

$$\text{Ideal Individual Dispersion} = \frac{1}{\Omega} - \frac{1}{N}$$

Building on this relationship, one can deduce the **ideal sample dispersion**. This is defined as the average deviation of the distribution, which in this context is equal to the following expression:

$$\text{Ideal Mean Deviation} = \frac{[(\frac{1}{\Omega} - \frac{1}{N}) \cdot \Omega] + [\frac{1}{N} \cdot (N - \Omega)]}{N}$$

This formula represents the **Ideal Mean Deviation** for an omega model, integrating both the contribution of the ideal subset (Ω) and the remainder of N.

47.12. Equivalent Forms of the Ideal Mean Deviation

The expression for the Ideal Mean Deviation can also be reformulated in more compact, symmetric forms. Specifically, it can be expressed as either:

$$\text{Ideal Mean Deviation} = \frac{[(\frac{1}{\Omega} - \frac{1}{N}) \cdot \Omega] \cdot 2}{N}$$

or, equivalently:

$$\text{Ideal Mean Deviation} = \frac{[\frac{1}{N} \cdot (N - \Omega)] \cdot 2}{N}$$

These alternative formulations show that the Ideal Mean Deviation can be understood either as the average of the double product of the Ideal Level of Bias by the number of ideals (Ω), or as the average of the double product of the inversion of N by the difference between N and Ω. Both perspectives highlight the dual contribution of the ideal and non-ideal subsets to overall sample dispersion.

47.13. Toward the Ideal Variance and Ideal Standard Deviation

If the Ideal Mean Deviation can be deduced, it logically follows that both the **Ideal Variance** and the **Ideal Standard Deviation** can also be derived. The Ideal Variance is obtained by dividing, by N, the result of adding two components:

1. The product of Ω multiplied by the square of the Ideal Level of Bias.
2. The product of the square of the inversion of N multiplied by the difference between N and Ω.

Formally expressed:

$$\text{Ideal Variance} = \frac{[\Omega \cdot (\frac{1}{\Omega} - \frac{1}{N})^2] + [(\frac{1}{N})^2 \cdot (N - \Omega)]}{N}$$

The **Ideal Standard Deviation** would then be defined as the square root of the Ideal Variance, thus completing the set of dispersion measures for omega models.

47.14. The Possibility of Rational Criticism in Omega Models

Once it becomes logically possible to deduce the **ideal dispersion**—whether at the individual or sample level—for a given N that contains an omega subset of ideals (between two and N minus one), the conditions are in place for **rational criticism**.

The various models of rational criticism have been presented in *Introduction to Impossible Probability: The Statistics of Probability or Statistical Probability*. At the **individual level**, one such model is the **Omega Validity**, already explained earlier in this blog. At the **sample level**, one example is the **Omega Sample Level**. These two

models represent the adaptation of rational criticism specifically to the structural conditions of omega models.

47.15. The Logic of Rational Criticism

The underlying logic of rational criticism is always the same: starting from a **maximum** or **ideal tendency**, the analysis establishes a margin of error or reliability within which the scientific community—or "scientific policy"—is willing to accept a given empirical dispersion, whether individual or sample-based.

The function of this logic is to transform an **empirical hypothesis** into a **rational hypothesis**, thereby granting it **provisional universal validity**. This is the epistemological purpose of rational criticism: to test the degree to which empirical distributions conform to their theoretical or ideal tendencies under accepted margins of error.

47.16. Rational Criticism in Normal Models

Within the so-called **normal models**—those in which the ideal is to tend either to maximum values or to minimum values—the **critical probability** or **critical ratio** is usually equal to the product of the maximum tendency by a given margin of error or reliability.

This margin is calculated as the quotient of the moral variable X (percentage of error or reliability) divided by one hundred. Formally:

$$p_c = T_{\max} \cdot \frac{X}{100}$$

Where: T_{max}= maximum tendency; X = percentage of error or reliability.

Accordingly, the model is accepted under two conditions:

- In **error studies, X = Error**, if the empirical value is equal to or less than the critical probability.
- In **reliability studies, X = Reliability**, if the empirical value is equal to or greater than the critical probability.

This logic applies straightforwardly to models where the maximum or minimum values represent the natural point of convergence for empirical distributions.

47.17. Rational Criticism in Omega Models

Omega models, however, are not normal in this sense. Their ideal condition is not to converge to a maximum or minimum, but rather to an **intermediate ideal value**. For this reason, rational criticism in omega models is not carried out with reference to maximum or minimum tendencies, but instead in relation to the **ideal values** of dispersion.

Thus, the rational criticism of **empirical dispersion** is conducted by evaluating empirical dispersion against a **critical margin** built on the basis of **ideal dispersion** (individual or sample).

- At the **individual level**, one example is the **Omega Validity**, which evaluates the deviation of empirical bias from the ideal level.
- At the **sample level**, one example is the **Omega Sample Level**, which is defined as the difference between the empirical Mean Deviation (or Standard Deviation) [and the **critical probability**.

The condition for acceptance is as follows:

$$\text{Omega Sample Level} = D_e - p_c \geq 0$$

where the critical probability is defined as:

$$\text{Omega Sample Level} = D_e - p_c \geq 0$$

with $D_i$representing the **Ideal Mean Deviation** (or Ideal Standard Deviation), and p_c is the critical probability with X as percentage of reliability.

If this condition is satisfied, the empirical model is accepted as rational within the specified margin of reliability.

47.18. Substituting Mean Deviation with Standard Deviation

In the following example, the analysis will be conducted using the **Mean Deviation (MD).** However, if the scientific policy requires the use of the **Standard Deviation (S)** instead, the procedure remains the same: one simply substitutes *Mean Deviation* with *Standard Deviation*, and *Ideal Mean Deviation* with *Ideal Standard Deviation*.

This flexibility ensures that the method of rational criticism can adapt to different statistical measures of dispersion, depending on the conventions or requirements adopted by the scientific policy.

47.19. Definition of the Omega Sample Level

The **Omega Sample Level**, when calculated on the basis of Mean Deviation (MD), can be formally expressed as follows:

$$\text{Omega Sample Level} = MD - p(x_c)$$

Acceptance condition:

$$MD - p(x_c) \geq 0 \Rightarrow \text{the empirical model is accepted.}$$

The **critical probability** p(xc) is defined by:

$$p(x_c) = \left(\frac{\left[\frac{1}{N} \cdot (N - \Omega)\right] \cdot 2}{N}\right) \cdot \left(\frac{X}{100}\right)$$

where:

- N= total number of subjects or options.
- Ω= number of ideal subjects or options within N.
- X= reliability percentage (moral variable).

This formulation expresses the way in which the empirical Mean Deviation is compared against a critical threshold that derives directly from the **Ideal Mean Deviation**, adjusted by the accepted percentage of reliability.

47.20. Distinguishing Normal and Omega Models in Rational Criticism

Within the framework of *Impossible Probability*, it is necessary to distinguish between two types of possible distribution models:

1. **Normal models**, in which the ideal is to tend toward maximum or minimum values.
2. **Omega models**, in which the ideal is to tend toward **omega-specific values**, that is, the probabilities and dispersions determined by the structure of the ideal subset Ω.

For each type of model, rational criticism must be adapted accordingly. In **normal models**, empirical hypotheses are evaluated in relation to extremes (maxima or minima), while in **omega models**, empirical hypotheses are evaluated in relation to **ideal values** that lie between those extremes.

The goal of rational criticism is to decide whether an **empirical hypothesis** can be accepted as **sufficiently rational**, within the error margin defined by scientific policy. This margin includes both:

- The **rational error**, deliberately fixed in the critical probability p(xc).
- The **factual error**, inherently accepted by the scientific community in the act of accepting the empirical sample itself.

In summary, unlike normal models, **omega models require specific rational criticism frameworks** adapted to the magnitude and structure of their ideals. These frameworks ensure that empirical results are judged not against extremes, but against intermediate ideal conditions characteristic of omega distributions.

Rubén García Pedraza, Madrid a 13 de enero del 2013

[History is a game, 13 January 1997]

This augmented translation is based on the post
published in https://probabilidadimposible.blogspot.com/,
On 13 January 2013,
Rubén García Pedraza
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48. The Functions of Error in the Statistics of Probability, or Statistical Probability, within *Impossible Probability*

In memoriam:

Stansfield Turner, January 18, 2018

William Egan Colby, May 6, 1996

"Along with several other Auschwitz doctors,

Mengele transferred to Gross-Rosen concentration camp

in Lower Silesia on 17 January 1945,

taking with him two boxes of specimens and the records of his experiments at Auschwitz. Most of the camp medical records had already been destroyed by the SS[80][81]"

Josef Mengele - Wikipedia

17 January, Cable Car Day

While officially the SS destroyed the remaining documents of Doctor Mengele, our strong opinion is that this did not happen. The SS took the documents of Doctor Mengele and reclassified them, probably through Operation Paperclip, Mind Kontrol Ultra, Operation Sunrise, or the Soviet counterpart, Operation Osoaviakhim. What in our opinion is clear is the remaining documents from the Nazi experiments in Dachau were taken by the OSS. The OSS interrogator in Dachau was J. D. Salinger, *The Catcher in the Rye*, Till today, neither the Pentagon nor the Capitol has revealed the nature of the interrogations carried out by Salinger in Dachau, which means that even now, 80 years later, these documents are still classified as *National Security*.

48.1. Probability as a Stochastic Model

Probability can be understood as a stochastic model of study. At its core, probability deals with the evaluation of the likelihood that a given event will occur, provided a set

of possible alternatives or options. To call probability *stochastic* is to emphasize its intrinsic connection with chance and randomness: it is not merely the enumeration of *possibilities*, but rather the systematic analysis of uncertainty itself. The notion of stochasticity implies that probability functions as a formalized inquiry into the role of chance within phenomena, structuring uncertainty into ***rational models*** that allow for prediction, measurement, and critical reflection. In this sense, probability is not a guarantee of outcomes but a framework for conceptualizing the inherent unpredictability of reality.

[Here the concept of possibilities is really important. Beneath the concept of subject or option, the synthesis of statistics and probability as Impossible Probability does, lies the idea that every subject or option is a possibility. In infinite universes, it is a possibility among many, tending toward infinity; in limited universes, it is a possibility within a finite scope. In the end, any subject or object is a possibility in descriptive, inferential, experimental, or quasi-experimental studies.]

48.2. Statistics as the Study of What Actually Happens

Statistics, by contrast, is the science of what has already occurred. It is fundamentally empirical, relying on the counting, *recording, and classification of frequencies and direct scores*. *From this empirical record emerge statistical measures,* ***data—whether individual or sample-based—which function as parameters to establish the rational boundaries of empirical or positive reality***. In other words, statistics provides the tools to delimit, with rigor, what can be asserted about reality as it unfolds.

Yet statistical knowledge is inevitably partial, because human cognition itself is partial. Human beings, by their finite condition, cannot know everything; they can only know what occurs within their own spatiotemporal context—within their *history*. Statistical data thus represent a *sample of history*: fragments of what reality shows of itself where and when the human observer happens to be.

This *process of recording* what happens can occur through *direct observation*—the immediate engagement of the senses—or through *indirect observation* mediated by

instruments. These instruments, ranging from microscopes to telescopes or devices for capturing radiation and deferred signals, extend perception beyond the spatiotemporal limits of the observer. Still, the ultimate source of all statistical data remains bound to human perception, either immediate or technologically extended, and therefore remains subject to the constraints of human finitude.

48.3. Social Mediation and the Transmission of Knowledge

Everything that does not arise directly from perception falls under the domain of *social mediation*. Social mediation refers to the transmission of knowledge, whether in the form of analytic or empirical history, natural or social sciences, or even myths, *legends*, and fables. In all cases, it is the passage of knowledge from one human being to humanity at large—knowledge that is either objective or subjective, but always previously elaborated.

The forms of this transmission evolve alongside humanity's technological development. In prehistoric times, knowledge circulated primarily through oral transmission. With the advent of writing, human societies entered the age of *historical record*. In contemporary times, transmission occurs through a multiplicity of media: digital storage systems, social networks, and mass communication platforms. Despite these technological transformations, the channels of reception remain the same: human sensory perception, whether visual or auditory.

Thus, whether the original source of knowledge is direct perception of a phenomenon, indirect perception through instruments, or mediated transmission through *social channels*, the process of knowledge remains fundamentally *physiological and perceptual*. Human physiology encodes sensory information into physiological signals, which are then synthesized by the brain. As such, all knowledge—whether direct, indirect, or socially mediated—is ultimately dependent on physiological, subjective, and empirical processes.

These processes provide the raw material for the formulation of hypotheses, which arise from the logical synthesis of perceptual premises, whether directly sensed or

mediated. From this point, *scientific policy* intervenes, deducing hypotheses and using them as the foundation for theories, models, and paradigms. Knowledge thus advances not as a simple reflection of external reality, but as a complex interaction of perception, physiological processing, social mediation, and rational deduction.

48.4. Statistical Probability as the *History* of Chance

If probability is the study of what occurs within chance, and statistics is the study of what actually happens, then *statistical probability*—the statistics of probability—necessarily becomes the study of what happens within chance over space and time. It is, in effect, the systematic examination of the *history of chance*.

This formulation *emphasizes* that probability, taken on its own, is abstract: it refers to potential outcomes and the logical *distribution of possibilities*. Statistics, by contrast, is concrete: it deals with realized events. By combining the two, one arrives at a framework that accounts for the unfolding of chance within history. Statistical probability is therefore not only a mathematical structure but also a historiographical method: it narrates the *history of the random*.

In this sense, statistical probability treats ***each recorded event not as an isolated fact*** but as part of a temporal sequence in which chance expresses itself. The "history of chance" is therefore identical with the "chance of history," because every historical event—whether large-scale or minuscule—carries within it a dimension of contingency that probability theory helps to articulate. What this synthesis makes clear is that chance itself is historically situated, and that the very occurrence of randomness is inseparable from the empirical unfolding of time.

[On the 13th of January 1997, before the events that will mark whole my life on the 17 of January 1997, I wrote a short document, it was the first time I used the expression "El Juego de la Historia", the game of History]

48.5. The Infinitude of the Universe and the Limits of Human Knowledge

History, understood as the *record* of what happens in *space and time*, can be conceived as the study of *spatiotemporal universes* from which samples are drawn. Were it possible to study history in its entirety, completely and consistently, such a study would encompass the totality of all events that have ever occurred within spacetime.

Yet this *project* confronts a decisive obstacle: the question of whether spacetime itself has an origin or an end. This problem leads directly to the transcendent inquiry of the universe's infinitude—the so-called *hypothesis of the infinite*. If the universe is infinite, then a finite, rational being such as the human subject cannot possibly comprehend it in its entirety. A finite nature, by definition, cannot contain the infinite. This line of reasoning, developed in *Introduction to Impossible Probability* (chapter seven), shows why complete and consistent knowledge is impossible for human cognition.

Alternatively, one could hypothesize that the universe, though not infinite, is so vast that its limits cannot be apprehended by human perception. But even if the universe were finite, that finitude would not automatically imply that human knowledge could be exhaustive or consistent. Human sensory and rational capacities are fundamentally limited. It is impossible for perception to grasp the infinite multiplicity of singular qualities that constitute reality. Consequently, what we know of the universe is never the whole but only *samples*—fragmentary glimpses filtered through our finite *perceptual apparatus*.

The paradox is that our very knowledge is determined by the samples we are able to extract from reality. The "sample of what we know" becomes, in effect, the limit of knowledge itself. Human understanding is bounded not by the absolute extent of the universe but by the fragmentary scope of what our condition allows us to perceive and record.

48.6. The Incompleteness of Mathematics and the Ideal of the Superman

The inconsistency and incompleteness of mathematics stem from the same human limitations. A being incapable of complete or consistent knowledge can only generate incomplete or inconsistent sciences. Mathematics, far from being the perfect universal

language it is often assumed to be, is in fact conditioned by the finite and partial nature of human cognition.

As long as humanity remains bound by its current condition, mathematics will hardly ever achieve the status of being either complete or fully consistent. Logical paradoxes, incompleteness theorems, and contradictions are symptomatic of this structural limitation. The only conceivable resolution would require the existence of a *superhuman intellect*—a "Superman" or an advanced form of Artificial Intelligence—that could know everything in an absolutely complete and consistent manner.

This imagined figure functions as a philosophical ideal: it points to a limit-concept of knowledge beyond human finitude. Until such a capacity exists, all mathematical and scientific knowledge must remain provisional, partial, and susceptible to revision.

[Here in this text from the 20th of January 2013, it is the first time I highlighted the possibility of a super machine — "súper sistema de Inteligencia Artificial, la súper-máquina." I need to say that at that time the idea of Superintelligence was not very popular, and even I had not read much about it, despite usually reading everything related to AI on social media and websites. This idea of the Supermachine is nothing other than our Global Artificial Intelligence. In this document, it is the first time I mention the possibility of building such a machine.]

48.7. The Sample as the Limit of Knowledge

In the absence of such a Superman—or a super-system of Artificial Intelligence, a "super-machine"—human knowledge is condemned to incompleteness. As long as not everything can be known, there will always remain inconsistencies, even if they are not immediately evident. Yet this limitation does not negate the pursuit of truth. On the contrary, over a sufficiently long or even infinite span of time, truth proves inevitable: whatever we now take as true but is actually false will eventually be refuted, and whatever we suppose to be false but is in fact true will eventually be confirmed, so long as scientific progress continues. Still, every truth under such conditions is only *provisional*.

This dynamic highlights what may be called the *transcendental contradiction of human knowledge*: a finite, physiological nature cannot know everything and therefore knows only a part. Human knowledge is forever conditioned by sampling. As emphasized throughout *Introduction to Impossible Probability*, the ideal would be to know the whole, but the limited human condition reduces knowledge to *samples of reality*. These samples—partial fragments of what occurs in history—constitute the *basis* of our understanding, and yet simultaneously delimit it.

Thus the sample is both the foundation and the limit of knowledge. It provides the empirical material upon which rational hypotheses are constructed, but it also defines the margin of error within which knowledge must operate. The fact that we can only ever know parts, never the whole, ensures that the very structure of human knowledge is provisional, incomplete, and historically bounded.

48.8. The Provisional Nature of Knowledge and Margins of Error

If we posit a possible universe of infinite singular qualities, then it follows that we cannot know all the particular details. What we access is only what the *sample* allows us to know. For this reason, human knowledge can never be considered absolutely universal; at best, it is provisionally universal. Knowledge is limited to what is included within the sample of what is observed and measured. For all that lies beyond the reach of the sample, hypotheses must be constructed.

These hypotheses are necessarily framed within margins of error. The *inversion of the sample*—that is, the mathematical representation of what is excluded or unknown—marks the structural boundary of empirical hypotheses. Within this framework, scientific policy admits empirical hypotheses as provisional truths, but always within the margin of error that critical reason dictates. Thus, every hypothesis is sustainable only in inverse proportion to the magnitude of accepted error. The larger the margin of error—whether factual or rational—the more likely it becomes that the accepted empirical hypothesis will be proven false the moment an event occurs that was not anticipated in the original sample.

In such a case, the hypothesis must be refuted and replaced with a new, more complex empirical hypothesis, one capable of integrating not only the original data but also the newly observed event or events. The history of science is marked by precisely this dynamic: provisional hypotheses being overturned and replaced by more comprehensive models that better account for reality.

Mathematically, the inversion of the sample may take different forms depending on the universe in question. For universes of infinite subjects or options, the inversion is expressed as the inversion of *N*. For universes of limited options, it is expressed as the inversion of direct scores or frequencies. In both cases, the inversion formalizes the principle that knowledge is bounded by what is excluded, and error is mathematically embedded in the very structure of statistical reasoning.

48.9. Models of Rational Criticism in *Impossible Probability*

The framework of *critical reason* depends upon the specific type of rational criticism applied. In *Impossible Probability*, these are divided into individual and sample-based models, as well as models oriented toward differential relations or ratio relations. The latter include *critical proportions*, which are explained in detail in section 11 of *Introduction to Impossible Probability*.

Among the individual-level models of rational criticism, several categories stand out:

- In studies of equality, the *Validity of Equality* and the *Significance of Equality*.
- In studies of bias, the *Validity of Positive Bias*, the *Validity of Negative Bias*, the *Significance of Positive Bias*, and the *Significance of Negative Bias*.
- In the family of omega models, the *Validity Omega*.

At the sample level, the models extend to collective or aggregate measures:

- The *Critical Sample Level of Equality* and the *Critical Sample Level of Bias*.
- In the omega category, the *Sample Level Omega*.

These models serve as methodological instruments for testing the rational soundness of empirical hypotheses, each with its own scope of application. Together, they constitute a *critical apparatus* that ensures statistical probability does not merely accumulate data, but actively subjects empirical knowledge to logical scrutiny, measuring its reliability against the unavoidable margins of error.

48.10. Provisionality and the Error of Fact in Science

The provisional character of knowledge is directly proportional to the margins of error—factual or rational—that science accepts. The *error of fact* refers to the margin of error that scientific policy must necessarily acknowledge when accepting the partiality of human knowledge, the *sample*. Since the *human condition* is limited, unable to encompass the totality of reality, it must resign itself to knowing only what can be known. This partiality renders every claim provisional: beyond the limits of the possible, nothing accepted as rationally true can in fact be true.

A sample, by definition, captures only a part of the whole. But the part is never the whole: at most it is representative, but never exhaustive. This contradiction is made explicit in *Introduction to Impossible Probability*: hypotheses constructed on partial samples are inevitably refuted whenever an unforeseen event occurs outside of the original selection. At that moment, the hypothesis collapses and must be reconstructed.

Thus the progress of science unfolds dialectically, through a cyclical process of provisional knowledge, refutation, and renewal. This is the movement from appearances toward light, from provisional conjecture toward more adequate rational truth. Yet the truth that emerges is never final; it always operates within the margin of error accepted by scientific policy.

In this way, the *error of fact* is not a defect but a structural condition of knowledge itself. It **signals** the limits of human finitude, ensures the critical revision of hypotheses, and defines science as a process of perpetual correction rather than as a body of eternal certainties.

48.11. Science as a Political Construction

The origin of error in the statistics of probability—or statistical probability—*arises from the contradiction between the finitude of human cognition and the infinitude* of what occurs in reality. Because an infinite number of events unfold, human beings, as finite observers, cannot possibly comprehend them all. Knowledge, therefore, can never grasp the totality of reality; it can only capture fragments—*what reality discloses of itself within the boundaries of our spacetime*, within our history, and within the limits of our cognitive sampling.

This limitation introduces what may be called the *first factual error of science*: the recognition that science is, by its very nature, partial. It is not a *universal mirror of reality* but a selective, situated enterprise. Science is historical, insofar as it always emerges within specific spatiotemporal and cultural contexts. For this reason, **science cannot be impartial or neutral** in the sense once idealized by the positivist paradigm.

Instead, science must be understood as *essentially political*. Scientific knowledge is shaped by the policies, priorities, and frameworks that determine what counts as valid inquiry, acceptable evidence, or legitimate explanation. In this sense, "science" is what *scientific policy* decides science to be. This does not diminish science's value, but it highlights its contingent and socially mediated *character*. The *neutrality* claimed by early positivism is an illusion; science is inseparable from the political conditions under which it develops, the interests it serves, and the institutional structures that govern its practice.

Thus, error in science is not merely a technical shortcoming but a reflection of the human condition: finite beings constructing knowledge in a world of infinite events. This partiality ensures that science is always political, provisional, and historically situated.

48.12. Rational Error, Nihilism, and Contingency

Just as the *error of fact* must be accepted as a consequence of the incomplete and inconsistent nature of human cognition, so too must a second type of error be

acknowledged: the *rational error*. This is the margin of doubt, skepticism, relativity, and uncertainty that arises from the exercise of critical reason. At its core, rational error represents a space of *incommensurability*—a zone where the very foundations of causal explanation may be destabilized.

If every possible causal explanation of reality is systematically placed into doubt, if every hypothesis is methodically questioned, and if every cause is perpetually contested, then what is ultimately placed in doubt is not merely this or that causal relation, but the very *idea of causality* itself. Within a sufficiently radical margin of uncertainty, it becomes conceivable that no true causes exist at all—that everything which occurs is merely accident, contingency, and the unfolding of chance.

From this perspective, science itself may appear as little more than a product of custom, a way of stabilizing expectations in a world without true causes. Beyond the limits of rational certainty, science must then admit a margin of *nihilism*: the recognition that every causal hypothesis is potentially false, and that in the long run—in infinite time—every causal explanation will inevitably be shown to be false. Rational analysis thus leads to a paradoxical conclusion: nothing is ultimately true.

Yet within this nihilistic contradiction, science retains its usefulness for life. Even if false in an absolute sense, science proves indispensable for survival. This paradox produces two divergent philosophical orientations. On one side, it leads to *moral utilitarianism* and *positivism*: science as a practical tool for managing life despite its provisional status. On the other, it points inexorably toward *vitalism*: the affirmation of life itself as the only ground of meaning, even in the absence of ultimate truth.

Thus, although we may know nothing definitive about life—whether each moment is unique and eternal, endlessly repeated across parallel universes, or one among *infinite possibilities*—***science still emerges as humanity's only means of ensuring survival*** in the struggle for existence. When confronted with the radical uncertainties of life, critical rationalism transforms into a radical vitalism. At this juncture, critical reason itself becomes philosophy in its most profound form: the confrontation with life's ultimate and unanswerable questions.

[At that moment, my vision was vitalist, very close to Nietzsche. The very idea of the supermachine as a replica of the Superman is, in fact, Nietzschean. In other words, we can understand GAI within postmodern theory if we assume Nietzsche as the prophet of postmodernity. On the other hand, even though we can identify the coming Superintelligence as an artificial replica of Nietzsche and place it within the logic of the "post"—especially within the discourse of post-humanism and post-industrialism—in reality, the mission of this supermachine is not truly postmodern. In the end, the true mission of this machine is the achievement of pure truth itself, even if it may not be fully possible because this machine will always be subject to the error of representativeness; it will still need samples to carry out any study of the universe. Yet even if this machine needs samples and the errors associated with sampling, as long as it is able to reduce data to a matrix of equations, the solution of that matrix should represent the reason for everything. In the end, this is the Holy Grail of positivism.]

48.13. The Gnoseological and Stochastic Functions of Error

Within the framework of statistical probability, or the *statistics of probability* as developed in *Impossible Probability*, error fulfills two fundamental functions: a **gnoseological function** and a **stochastic function**. These two dimensions of error are not merely technical; they embody the very conditions under which knowledge and science operate.

The **gnoseological function** of error corresponds to the *error of fact*. It arises from the recognition that human beings cannot know anything without an accompanying margin of error. Indeed, what seems impossible may nonetheless prove inevitable if it falls within a logically coherent margin of error. In this sense, error is not a flaw but the very horizon of knowledge. The extent of our knowledge is inversely proportional to what we do not know, and what we do not know is directly proportional to the size of the error margin. One of the principal functions of this margin—formalized mathematically through the error of fact—is to determine the probability of refuting a hypothesis, based on the proportional part of the universe that remains unknown. This is what *Impossible*

Probability terms the **inversion of the sample**: the mathematical mechanism by which ignorance itself is quantified and integrated into rational models.

The **stochastic function** of error, by contrast, corresponds to the *rational error*, the domain of critical reason. It constitutes the foundation of indeterminism in science. If the inversion of the sample (the error of fact) represents the probability that a hypothesis will be refuted because it excludes unknown phenomena, then rational error introduces a further dimension: systematic doubt about causality itself. Provisional hypotheses, though accepted as universal, are constructed from limited samples. When reason critically extends skepticism to all causal relations, what is ultimately questioned is not only particular causes but the very *idea of cause*.

From this perspective, rational error opens a horizon in which perhaps no cause is ultimately true, and everything happens inexorably by chance. **Within such a margin of rational error, everything may be regarded as mere accident or contingency**. Rational error, then, becomes the acceptance by scientific policy of a necessary margin of nihilism. It acknowledges the logical–dialectical contradiction that **knowledge may be false and yet still useful.**

This paradox secures ***the pragmatic role of science: even if its explanations are not ultimately true, they remain indispensable for the survival of humanity***. Here the ethical dimension of science emerges. For *rational error to remain viable, scientific policy must exercise responsibility*: it must operate with sufficient logical rigor and ethical awareness in its decisions. Thus, the stochastic function of error not only grounds indeterminism but also introduces a moral imperative, reminding us that scientific practice, however provisional or contingent, must be oriented toward ***human survival and the preservation of life.***

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493. Empirical Reality and Theoretical Reality

493.1. Reality as a Historical and Chaotic Nature

Reality is everything that happens, and its principal characteristic is that it is of a **historical nature**. It consists of an indefinite set of phenomena that occur randomly and variably across space and time. These phenomena unfold in cycles that are both unpredictable and unstable—except within the critical margin of error that rational critique allows. Reality is therefore made up of accidents and contingencies that generate, without systematic design, temporary and perishable patterns of apparent *regularity*.

In this sense, reality is the chaotic and nonlinear unfolding of matter. What we truly know is that "things happen"; we intuitively sense that events are taking place, though we seldom know with precision *what* they are. From these events—phenomena that happen in reality—emerge possibilities that mathematics seeks to formalize in terms of probability. What we aim to achieve, at minimum, is a *basic comprehension* of these possibilities.

However, knowledge can never be absolute. Any form of possible knowledge will always be constrained by the limits of scientific reliability, which itself is provisional and rational only within certain margins. Beyond these margins, knowledge becomes subjective and temporally bounded, *highlighting the fragile and contingent character of all human understanding*.

493.2. Events as the Definition of Reality

What occurs—events or happenings—is what gives shape to reality and defines it. Reality is not an abstract entity detached from phenomena; it is the very collection of occurrences that constitute existence. This definition applies whether we are speaking of a *particular reality* under study—an isolated domain of inquiry—or of reality in its **holistic sense**, as the totality of all events across all possible histories, the *universal history*.

Yet science never studies the total absolute of anything. It cannot, because human inquiry is bound to partial access. Science works with *samples*—selections of universes or entire populations taken as objects of study, and these samples are themselves fragments of history. The act of sampling both defines and limits the scientific object: reality becomes scientifically knowable only as a *portion* of the whole.

493.3. Measurement of Reality as the Basis of Knowledge

If the object of knowledge is the study of reality itself, then any attempt to obtain the most objective form of knowledge possible—particularly when formulated mathematically—must begin with **measurement**. Measurement constitutes the first step in the translation of reality into scientific terms. Its outcome is what we call *empirical reality*: the form in which reality becomes objective within human subjectivity, mediated by the mind.

This does not mean that reality is reducible to our perception, but rather that reality only becomes accessible to science through the act of quantification. Measurement provides the bridge between what happens and what can be known, transforming the flux of phenomena into discrete data that can be studied, compared, and theorized. Without measurement, there can be no scientific object, only unarticulated experience.

493.4. Measurement in Statistics and Probability

In the fields of statistics and probability, measurement takes on a precise form. It produces either **direct scores** or **frequencies**, depending on the type of events under study. If the object of study requires quantifying the *magnitude of intensity* in individual elements or subjects selected for investigation, the outcome will be a *direct score*. This represents the measured intensity of a given attribute within each subject or event.

Alternatively, if the universe of study is composed of a limited set of possible options, measurement results in the quantification of **occurrences**. In this case, the measurement expresses how many times each option occurs within the sample. The sum of all occurrences across the options equals the total frequency for that universe.

Through this process, reality is given form as empirical data. Measurement thus constitutes the foundational step that transforms reality into a domain that can be analyzed by statistical and probabilistic methods. It turns the unpredictability of events into structured representations that, although provisional, make possible the development of rational models of knowledge.

493.5. Measurement as the First Instance of Empirical Knowledge

If reality is what happens, then empirically, the first thing that science knows about what occurs is whatever **measurement** indicates has taken place. Measurement thus constitutes the initial and indispensable instance of empirical knowledge. Yet this first step is itself fragile, for it is always subject to **sampling error**. In *Impossible Probability*, this limitation is expressed through the concept of the *inversion of the sample*: the recognition that what we know empirically is never the whole, but only a fragment, and that this fragment is necessarily prone to error.

This inversion of the sample is not accidental but structural; it reveals the random function of error in human knowledge. Measurement does not eliminate uncertainty—it formalizes it. What science captures is not pure reality but the mediated trace of

reality within the confines of a sample, already circumscribed by the margins of error that accompany all observation.

493.6. The Sample as the Limit of Empirical Knowledge

Reality is therefore defined as what happens. However, of all that happens, we only ever know the *sample*. And from the sample, empirically, we only know what measurement reveals. This is expressed in the form of **direct scores** or **frequency tables**.

Direct scores correspond to the measured intensity of the attribute under study in individual elements—the subjects of observation—within infinite universes. Frequencies, by contrast, correspond to the number of occurrences of each option in universes with limited alternatives. In both cases, the sample—whether made up of scores or frequencies—constitutes the empirical reality that science can access.

From this starting point, *Impossible Probability* transforms empirical reality into a system of **statistics or probabilities**. The sample becomes more than a mere collection of observations: it becomes the mathematical substrate for probabilistic reasoning. Still, the boundary remains: what is known is only what is sampled, and the sample itself is never identical with the whole of reality.

493.7. Methods of Study in *Impossible Probability*

Empirical reality is thus equivalent to the measurement of reality, which mathematically creates a sample of observations and measurements. **This sample is susceptible to statistical or probabilistic study**. Within *Impossible Probability*, several synthetic methods are available for such study, the principal ones being:

- the **Second Method**,
- the **Impact of the Defect**, and
- the **Effective Distribution**.

Each of these methods provides a different perspective on how to treat empirical data within rational frameworks. The *Impact of the Defect* is explored in section 21 of *Introduction to Impossible Probability*, while the *Effective Distribution* is treated in section 22. The *Second Method*, by far the most central, is elaborated throughout much of the work. For the study of **individual statistics**, particular attention is recommended to sections 3, 8, and 11.

These methodological options highlight that the path from empirical measurement to theoretical knowledge is neither singular nor automatic; it is mediated by diverse rational strategies that seek to minimize error and extend the reach of provisional knowledge.

493.8. Transformation of Samples into Empirical Probabilities

Within the Second Method of *Impossible Probability*, the transformation of raw data into probability takes a precise form. Tables or samples of direct scores or frequencies—whether drawn from subjects or options—are converted into **empirical probabilities**.

This is achieved by dividing the direct score or frequency of each subject or option by the total sum of scores or frequencies across the entire sample. The formula is valid for all types of universes, whether infinite or limited. In this way, empirical probability becomes a normalized representation of the distribution of events.

The transformation is crucial because it converts raw measurement into a rational structure: a framework in which empirical reality can be *compared, analyzed*, and subjected to theoretical *critique*. From this point, the science of probability ceases to be only descriptive and becomes an interpretive system, capable of generating critical models of knowledge that integrate both empirical data and theoretical ideals.

493.9. The Difference Between Simple Reality and Empirical Reality

The definition of *empirical reality* depends directly on the level of mathematical complexity with which it is formulated. At the most *basic level,* reality can be defined as a **simple enumeration** or list of *observations, measurements, or raw data*. At a more advanced level, however, reality can be elaborated statistically or probabilistically. In the latter case, reality ceases to be merely a set of observed events and becomes *empirical reality*, understood as what mathematics and probability can say about what happens.

The distinction, then, is fundamental: **reality** is what happens, while **empirical reality** is what measurement, statistics, and probability allow us to infer about what happens. This transformation from *reality [The real world itself*, outside of ourselves] into *empirical reality [The world as it appears to us*, through our natural senses or through artificial sensors and instruments of measurement] requires a crucial admission: all mathematical elaboration of reality is bounded by error margins. Science cannot claim to know with absolute certainty what happens in reality; it can only offer what is empirically accessible.

Thus, empirical reality must be recognized as a provisional construct, composed of **samples of reality**. These samples, in turn, are subject to statistical and probabilistic investigation, particularly through the framework of *Impossible Probability*. There, empirical reality is studied as *statistical probability*: a rational system that critically relates measurement, error, and theoretical ideals.

493.10. Empirical Statistics for Understanding the Structure of Reality

Once empirical reality is defined through a system of probabilities, it becomes possible to construct **empirical statistics** in order to reach greater depth in understanding its structure. These statistics fall into two main categories: **individual statistics** and **sample statistics**.

Within the *Second Method of Impossible Probability*, one can calculate the empirical probability of each subject or option in a sample. This makes it possible to identify:

- the **maximum empirical probability** ("p(xi+)"), corresponding to the subject or option with the greatest probability in the sample,
- the **minimum empirical probability** ("p(xi-)"), corresponding to the subject or option with the smallest probability in the sample, and
- the **intermediate probability** ("p(xi+/-)"), defined as the mean point between the maximum and the minimum.

The intermediate probability is calculated by dividing by two the sum of the maximum and minimum values. These measures—maximum, minimum, and intermediate—allow the structure of the sample to be interpreted not only in descriptive terms but also in relation to theoretical ideals, such as equality, bias, or dispersion.

Through these statistics, empirical reality acquires form and hierarchy. It is no longer an undifferentiated set of occurrences but a structured domain where probabilities reveal tendencies, disparities, and potential norms.

493.11. Theoretical Reality in Contrast to Empirical Reality

The moment empirical reality can be defined, it becomes possible to define **theoretical reality** as well. One of the distinctive features of *Impossible Probability* lies precisely in this duality: for every empirical value obtained through measurement, there exists a corresponding **theoretical value**.

If empirical probability is calculated as the direct score or frequency of a subject or option divided by the total of scores or frequencies in the sample, then theoretical probability is defined in an invariant way: as the *inversion of N* (1/N). This holds for all possible universes, whether finite or infinite. Theoretical probability represents the probability of occurrence *by pure chance*.

Theoretical reality thus functions as a **rational counterpoint** to empirical reality. It does not describe what happens, but rather what *should* happen under conditions of pure

equality and randomness. Its role is critical: by comparing empirical data with theoretical distributions, one can measure bias, inequality, or deviation.

This contrast between empirical and theoretical reality is one of the pillars of *Impossible Probability*. It ensures that knowledge is never reduced to description alone, but is always tested against **rational ideals**. The relationship between what happens (empirical reality) and what should happen (theoretical reality) defines the margin within which science operates and error becomes meaningful.

493.12. Theoretical Limits of Empirical Probability

If the maximum empirical probability is equal to the highest probability observed in the sample, then **the Maximum Possible Empirical Probability** is, by definition, the value of one. No empirical probability can ever exceed unity, since probability expresses the proportion of occurrence within the total and is bounded by 0 and 1.

Conversely, if the minimum empirical probability is equal to the lowest probability in the sample, then **the Minimum Possible Empirical Probability** must, in theoretical terms, be zero. It would be irrational, and mathematically inconsistent, for a positive event to have a negative empirical probability. Thus, probability theory recognizes absolute boundaries: one as the maximum and zero as the minimum. These are not merely conventions but structural necessities of rational measurement.

493.13. The Theoretical Intermediate Probability

Once the upper and lower limits are established—unity as the maximum and zero as the minimum—the **Theoretical Intermediate Probability** follows directly. It is calculated as the mean of the two extremes:

$$\text{Intermediate Probability} = \frac{1+0}{2} = \frac{1}{2}.$$

This value, one-half, functions as the midpoint of the probabilistic scale. It represents theoretical balance, the central position between complete certainty and complete impossibility. The concept is significant because it provides a rational benchmark against which empirical distributions may be compared, highlighting tendencies toward concentration or dispersion relative to equilibrium.

[Intermediate Probability is only useful in normal models of positive bias whose aim is to concentrate all probability in a single subject or option as the ideal, with the rest of the subjects or options equal to zero. In these models, as long as the ideal subject or option is above the Intermediate Probability, and the remaining N-1 subjects or options are below the Intermediate Probability, it is a clear sign that the model tends toward maximum dispersion.]

493.14. Transformation of the Second Method into Levels of Bias

In the *Second Method of Impossible Probability*, traditional differential scoring in statistics is reformulated into what is termed the **Level of Bias**. This is defined as the difference between empirical probability and theoretical probability:

$$\text{Level of Bias} = p(\text{empirical}) - p(\text{theoretical}).$$

Within this framework, the **Maximum Theoretical Bias Possible** is equal to the difference between one (the maximum probability) and the inversion of N (the theoretical probability, **the inversion of N subjects or options**). Meanwhile, the **Maximum Negative Bias Possible** is equal to the inversion of N itself.

This redefinition is crucial, as it shifts the focus of statistical analysis away from raw deviations and toward a structured evaluation of how far empirical results diverge from theoretical expectations. The language of “bias” thus emphasizes the critical

dimension of probability: the constant measurement of disparity between what *is* and what *should be*.

493.15. Theoretical Value in Contrast to Empirical Value in *Impossible Probability*

The principal feature of *Impossible Probability* is that for every empirical value there always exists a corresponding **theoretical value**. This duality ensures that knowledge is never purely descriptive but always accompanied by a rational counterpart.

For example, once the Maximum Possible Empirical Probability is identified, one can also deduce the **Maximum Possible Empirical Bias**, the **Maximum Theoretical Bias**, and the **Maximum Negative Bias**. From these, further theoretical quantities can be derived, such as:

- the **Maximum Theoretical Mean Deviation**,
- the **Maximum Theoretical Variance**, and
- the **Maximum Theoretical Standard Deviation**.

These measures are indispensable for the study of **normal models**—those in which dispersion ranges between zero and its maximum—depending on the object of study. In this way, *Impossible Probability* offers a comprehensive framework in which every empirical observation is accompanied by its theoretical ideal, and every deviation is framed within rational bounds.

This dialectic between the empirical and the theoretical lies at the core of the system. It affirms that science must not only describe what occurs but also measure the distance between the real and the ideal, between the contingent data of history and the rational structures that give them meaning.

Empirical Reality or Empirical Statistics	Theoretical Reality or Theoretical Statistics
Empirical Probability = p(xi) = xi / Σxi	Theoretical Probability = 1/N
Maximum Empirical Probability = p(xi+)	Maximum Possible Empirical Probability = 1
Minimum Empirical Probability = p(xi-)	Minimum Possible Empirical Probability = 0
Intermediate Probability = p(xi+/-) = (p(xi+) + p(xi-)) : 2	Theoretical Intermediate Probability = (1 + 0) : 2 = 0,5
Maximum Possible Empirical Bias= Σ ((xi) – 1/N) : 2	Maximum Possible Theoretical Bias = (1 – 1/N) Maximum Possible Negative Bias=

	/ (0 – 1/N) / = 1/N
Mean Deviation = $\Sigma (p(xi) - 1/N) : N$	Maximum Possible Theoretical Mean Deviation = $[(1 - 1/N) \cdot 2] : N$
Variance= $\Sigma (p(xi) - 1/N)^2 : N$	Maximum Possible Theoretical Variance= $\{ (1 - 1/N)^2 + [(1/N)^2 \cdot (N - 1)]\} : N$
Standard Deviation = $\sqrt{[\Sigma (p(xi) - 1/N)^2]} : N$	Maximum Possible Theoretical Standard Deviation = $\sqrt{\{\{ (1 - 1/N)^2 + [(1/N)^2 \cdot (N - 1)]\} : N\}}$

493.16. Empirical and Theoretical Definition of Reality

Once an **empirical definition of reality** has been achieved, it becomes possible to advance toward a **theoretical definition of reality**. The empirical level establishes what can be measured, quantified, and statistically analyzed, while the theoretical level articulates rational ideals that transcend the limitations of immediate measurement. This progression from the empirical to the theoretical is not optional but intrinsic to the scientific method as conceived in *Impossible Probability*.

493.17. Individual Statistics as an Approximation to Reality

The individual statistics defined so far represent only an **approximation** to what would ultimately constitute a full empirical or theoretical definition of reality. They are preliminary tools that serve to describe and partially interpret the structure of phenomena but cannot by themselves capture the whole. Their value lies in their capacity to function as building blocks—indicators that orient research toward more comprehensive theoretical models.

493.18. Normal Models and the Theoretical Development of Research

In the case of **normal models**, statistical elaboration implies the development of theoretical structures in accordance with the **objectives and ideals of research**. Here, theory guides empirical practice: the purpose of the investigation determines which measures of equality, bias, or dispersion are to be emphasized, and how results are interpreted. Thus, normal models embody the dialectical relation between the descriptive level of empirical reality and the normative level of theoretical ideals.

493.19. Omega Models in *Impossible Probability*

The case of **omega models**, explained in sections 11 and 20 of *Introduction to Impossible Probability*, provides a more complex scenario. Omega models are defined as those in which the magnitude of ideals oscillates between two and $N-1$. They therefore occupy a middle ground between the extremes of absolute equality and absolute concentration. Their analysis requires a distinct methodological approach, since the distribution of probabilities cannot be reduced to either purely normal or purely singular cases.

[Our attention must be brought to the fact that in the end the whole organization of our investigation depends on two ultimate factors, our ideals and the universe itself]

493.20. Theoretical Statistics and Dispersion in Omega Models

In omega models, *the relevant focus lies in the construction* of **theoretical individual statistics** and measures of **theoretical dispersion**. These quantify the way in which multiple ideal subjects or options distribute themselves within the space between two and $N - 1$. The challenge is to integrate these measures into a coherent theoretical framework capable of accounting for partial concentrations of probability without collapsing into the extremes of unity or zero.

Thus, omega models highlight the richness of *Impossible Probability*: they show that reality is not confined to binary oppositions of equality and singularity but admits intermediate configurations where ideals are plural and dispersion acquires a more nuanced structure.

[The discussion regarding binary logic, if in essence it has been brought forth by postmodern philosophy, is not presented here as a postmodern interpretation of science. Rather, it is simply the realization that between the extremes—one subject or option concentrating all the data, or, on the opposite end, dispersion equal to zero—there is room for third, fourth, and even nth models in which we can organize our ideals. In other words, there is always at least a third way, at minimum.]

Theoretical Statistics in Omega Models
Ideal Probability = 1/Ω
Ideal Bias Level = 1/Ω - 1/N
Ideal Mean Deviation = { [(1/Ω - 1/N)] · 2 } : N

Ideal Variance = $\{ \{ [(1/\Omega - 1/N)^2] \cdot \Omega \} + [(1/N)^2 \cdot (N - \Omega)] \} : N$
Ideal Standard Deviation = $\sqrt{\ } \{ \{ [(1/\Omega - 1/N)^2] \cdot \Omega \} + [(1/N)^2 \cdot (N - \Omega)] \} : N$

493.21. The Importance of the Theoretical Definition of Reality

The **theoretical definition of reality** is of crucial importance, because it always depends on the object of study, which in turn is shaped by the *political theory of science*. Every scientific investigation is designed with a specific purpose, and that purpose is political in the broadest sense: it reflects the ends for which knowledge is produced. The theoretical definition of reality therefore functions as the axis where epistemology meets political intention, determining what is to be studied, how it is to be studied, and for what it is ultimately intended.

493.22. The Relationship Between Empirical and Theoretical Statistics

In theoretical terms, empirical and theoretical statistics must be brought into relation with one another. This duality ensures that science does not simply describe what is observed but also evaluates it against rational ideals. For **normal models**, the objects of study may be equality, positive bias, or negative bias. For **omega models**, by contrast, the focus shifts to the equal increase of subjects or options included within the omega structure. In both cases, the articulation between empirical measurement and theoretical expectation allows for the critical testing of knowledge.

493.23. Normal Models and the Object of Study

In a **normal model of equality of opportunity**, the identity between all empirical probabilities and their theoretical counterparts implies that the theoretical aim of

research is moral as well as scientific: that the behavior of every subject or option converge toward equality of opportunity. In this case, the theoretical objective of the project is that both **individual empirical dispersion** (the Level of Bias) and **sample dispersion** (Mean or Standard Deviation) tend toward zero.

By contrast, in normal models where the object is the maximization of inequality—where in a given universe N, only one subject or option is expected to approach the highest possible bias—the theoretical ideal is different. Here, the empirical probability of the ideal subject or option should tend toward the **Maximum Possible Empirical Probability**. Consequently, individual dispersion tends toward the **Maximum Theoretical Bias Possible**, while sample dispersion tends toward the **Maximum Theoretical Mean or Standard Deviation Possible**. Thus, the choice of object of study radically shapes the theoretical structure of the model.

493.24. The Sample as the Limit of Possible Knowledge

Reality, in its fullness, is everything that happens. Yet of all that happens, we never know absolutely everything. What we know is only a **part**—the *sample*—and from that sample, empirical reality is constructed. Measurement is therefore the origin of all possible knowledge, but its reach is bounded.

This process of measurement comprises different levels of elaboration. At the most basic level, it involves the quantification of what happens through **direct scores** or **frequencies**. At higher levels, empirical content is transformed into **statistical tables** or **probability models**. At each stage, however, the sample remains the limit: it provides access to reality, but only in fragments. Science is therefore built on partial access to reality, mediated by measurement and formalized mathematically.

493.25. Forms of Understanding Theoretical Reality

Theoretical reality, by contrast, admits multiple forms of understanding. On the one hand, it may consist of a simple theoretical definition of reality expressed through **theoretical statistics**—whether individual or sample-based. On the other hand, it may

involve a deeper definition of reality that incorporates the **objectives and aims of scientific investigation**, understood in accordance with the ideals of scientific policy.

Thus, theoretical reality may reflect:

- the implementation of a policy of equality within the sample, extrapolated to the population or universe from which the sample was drawn; or
- the implementation of policies of **individual improvement**, designed to enhance empirical performance in direct scores or frequencies of particular elements or options.

In either case, the ideals are not neutral but politically defined. The ideology underlying scientific policy determines what is considered "ideal," and therefore sets the objectives and ends of science itself. Theoretical reality is thus inseparable from the political dimension of knowledge: it is the *projection of rational structures guided by normative commitments*.

This augmented translation is based on the post
published in *https://probabilidadimposible.blogspot.com/*,
On 3 February 2013,
Rubén García Pedraza
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49. Statistical Dispersion, Normal or Relative

49.1. On the Difference Between Normal or Relative Statistical Dispersion

49.1.1. The Differentiation of Types of Statistical Dispersion

Within the study of **statistical dispersion**, it is essential to differentiate between several types. In *Introduction to Impossible Probability* (section 14), various models of **relative statistics** are explained, which contrast with the framework of normal statistics. These distinctions are necessary because dispersion does not have a single form; *it depends on the reference point adopted and on whether the statistical method remains tied to the classical mean or moves beyond it into alternative formulations*.

49.1.2. Normal Statistics versus Relative Statistics

Traditional statistics, as it has been historically practiced, is always **normal statistics**. This is because it exclusively understands dispersion through the calculation of **differential scores relative to the arithmetic mean**. The Second Method of *Impossible Probability*, however, opens the possibility of **alternative statistics**, in which dispersion is not necessarily calculated with reference to the arithmetic mean. These alternatives are collectively referred to as **relative statistics**, because they allow for differential comparisons against values other than the mean, such as theoretical or ideal probabilities.

49.1.3. The Principle of Dispersion: Individual and Sample Levels

The study of dispersion begins with the **differential behavior of any subject or option** with respect to a chosen reference probability—whether theoretical, ideal, or empirical. This form of dispersion, originating from each subject or option, is known as **individual dispersion**. Depending on the reference point, it can be classified as either normal or relative.

From individual dispersion, one then derives **sample dispersion**, which aggregates the differentials of individual elements. Sample dispersion too can be normal or relative, depending on the statistical framework applied. In this sense, dispersion is not a monolithic measure but a layered process: *it begins with individual behavior and culminates in collective tendencies*.

49.1.4. Normal Dispersion as the Default Form

Unless otherwise specified, any reference to "dispersion"—whether individual or sample-level—should be understood as **normal dispersion**. Normal dispersion is defined as the differential behavior of **empirical probability minus theoretical probability**, where theoretical probability is represented by the inversion of N(1/N).

In this framework, the **origin of all statistical dispersion** is the individual dispersion. The average of these individual dispersions forms the basis for the study of sample dispersion. Specifically, the origin of normal dispersion is the **Level of Bias**, which measures the difference between empirical and theoretical probabilities. This makes the Level of Bias the foundation upon which all normal dispersion is constructed.

49.1.5. The Role of the Arithmetic Mean in Normal Dispersion

In *Impossible Probability*, whenever dispersion is mentioned without qualification, it typically refers to normal dispersion. This is because, unless stated otherwise, dispersion within a sample is calculated with reference to the **arithmetic mean**. The

mean of empirical probabilities, by definition, coincides with the theoretical probability—again, the inversion of N. This highlights the multifunctional role of the inversion of N, which operates simultaneously as a measure of theoretical probability, as a reference point for bias, and as the baseline for normal dispersion.

49.1.6. Distinguishing Normal and Relative Dispersion

To classify different types of dispersion, it is not enough to distinguish only between **theoretical versus empirical dispersion**, or between **individual versus sample dispersion**. A more fundamental distinction must be drawn between **normal dispersion** and **relative dispersion**.

This difference is not merely terminological but methodological. It reflects two distinct types of statistics:

- **Normal statistics**, which measure dispersion relative to the arithmetic mean and theoretical probability.
- **Relative statistics**, which measure dispersion relative to other reference values, opening the possibility of alternative models that challenge the monopoly of the mean in statistical reasoning.

This distinction expands the epistemological scope of statistics, situating *Impossible Probability* as a framework that acknowledges both traditional and innovative forms of dispersion, each corresponding to different ways of understanding variability in empirical and theoretical contexts.

2. Normal Statistical Dispersion, Individual or Sample-Based, Empirical

49.2.1. Normal Statistics as Reference to the Arithmetic Mean

By *normal statistics* is understood that form of statistics which takes the **arithmetic mean** as its reference point. In the **First Method** (section 4), this is the classical form of

statistics: dispersion is calculated from the differences of scores relative to the mean. In contrast, in the **Second Method of Impossible Probability** (section 3), the reference is no longer the arithmetic mean of direct scores but rather the **inversion of N (1/N)**. Within this framework, **normal empirical individual dispersion** is defined as the **normal Level of Bias**.

Thus, in the Second Method, normal statistics are structured around **theoretical probability** as the axis of reference. By contrast, **relative statistics** are defined as those in which the reference point is any empirical, ideal, or theoretical value other than the inversion of N.

49.2.2. Normal Statistics as the Default Case

Unless otherwise specified—such as when explicitly discussing relative statistics—whenever *Introduction to Impossible Probability* refers to statistics or dispersion, it refers to **normal statistics** or **normal dispersion**.

Within normal statistics, it is necessary to distinguish between:

- **Individual dispersion** and **sample dispersion**; and within each of these,
- **Theoretical dispersion** and **empirical dispersion**.

The empirical origin of all dispersion is individual dispersion, which is grounded in the **normal Level of Bias** (or simply *Level of Bias*). Unless otherwise indicated, the term *Level of Bias* must always be understood to mean the normal Level of Bias, as this is the default case in a normal statistical model.

49.2.3. The Level of Bias as the Basis of Empirical Dispersion

The **normal Level of Bias**—defined as the difference between empirical probability and theoretical probability—is the foundation of all empirical dispersion. From it, **normal sample dispersion** (or simply sample dispersion) is derived.

Sample dispersion integrates the classical measures:

- **Mean Deviation**,
- **Variance**, and
- **Standard Deviation**.

Normal Mean Deviation is the average of the sum of the absolute values of the normal Levels of Bias. In essence, the sum of all Levels of Bias is the **Total Bias**. Therefore:

$$\text{Mean Deviation} = \frac{\text{Total Bias}}{N} = \text{bias by chance} = \text{chance by bias.}$$

The order of the factors does not alter the product: Mean Deviation is essentially the product of bias and chance. This fundamental identity is developed in section 13 of *Introduction to Impossible Probability*.

49.2.4. Variance and Standard Deviation in the Second Method

In traditional statistics (the First Method), the preferred way to neutralize negative signs in differential scores is to **square** them, thereby ensuring that the sum of differentials is not zero. This results in **Variance**, which is the quadratic estimation of sample empirical dispersion.

Transposed into the Second Method, this becomes the **average of the squared Levels of Bias**. Subsequently, because differential scores (First Method) or Levels of Bias (Second Method) are not themselves squared when used in final comparisons, it is necessary to take the **square root of the Variance** to make results comparable. The result is the **Standard Deviation**.

In *Impossible Probability*, Standard Deviation is central to the construction of **Typical Score models**, and their respective forms of **rational criticism**, which are notably distinct from traditional models. These are explained in detail in section 15.

49.2.5. Theoretical Dispersion in Normal Statistics

While **empirical normal individual dispersion** is expressed by the Level of Bias, and **empirical normal sample dispersion** by Mean Deviation, Variance, and Standard Deviation, the estimation of **theoretical dispersion** (individual or sample) depends on the type of universe under study.

Impossible Probability distinguishes between:

- **Universes of infinite subjects or options**, and
- **Universes of limited options**.

This differentiation is crucial, because the calculation of theoretical dispersion changes according to the type of universe.

49.2.6. The Multifunctionality of the Inversion of N

The **inversion of N (1/N)** must be treated with special attention due to its **multifunctionality**. It acts simultaneously as:

- the **theoretical probability of occurrence by chance under equality of opportunities**,
- the **arithmetic mean of empirical probabilities**,
- the **probability of sampling error** and the **probability of theoretical dispersion** only in infinite universes

In infinite universes, 1/N measures both error and theoretical dispersion. In limited universes, however, these same functions (error and theoretical dispersion) are fulfilled by the **inversion of the sum of direct scores or frequencies**, expressed as:

$$\frac{1}{\Sigma x_i}.$$

49.2.7. Sample Size and Theoretical Dispersion

The reason why the inversion of the selected sample—whether 1/N in infinite universes or 1/Σxi in limited universes—represents **the probability of theoretical dispersion** lies in the relationship between sample size and representativity.

- As the sample size increases, the probability of sampling error decreases, and the empirical probabilities tend to converge toward the theoretical probability (1/N).
- Consequently, larger samples imply a higher probability of achieving **zero Level of Bias** and thus lower dispersion.
- Conversely, smaller samples imply a higher probability of dispersion.

Therefore, the probability of theoretical dispersion is **inversely proportional to the sample size**: the smaller the sample, the higher the probability of theoretical dispersion; the larger the sample, the lower that probability.

49.2.8. Empirical and Theoretical Dispersion Compared

It is crucial to note that a higher or lower probability of theoretical dispersion does not automatically entail higher or lower empirical dispersion. For example*, in a sufficiently representative study of bias, increasing the sample size improves reliability, but empirical dispersion may still increase if the experimental variable impacts the ideals positively.*

In essence:

- The **normal Level of Bias** measures **individual empirical dispersion**.
- **Mean Deviation, Variance, and Standard Deviation** measure **sample empirical dispersion**.

- The **inversion of the sample**—1/N in infinite universes or 1/Σxi in limited universes—measures **theoretical dispersion and empirical error (the sampling error)**.

49.2.9. The Maximum Statistical Values of Normal Dispersion

Once empirical and theoretical dispersions have been determined—through either individual or sample statistics—it is possible to establish the **maximum statistical values** of dispersion. These include:

- At the **individual level**:
    - Maximum Theoretical Bias Possible,
    - Maximum Negative Bias Possible.
- At the **sample level**:
    - Maximum Theoretical Mean Deviation Possible,
    - Maximum Theoretical Variance Possible,
    - Maximum Theoretical Standard Deviation Possible.

These measures provide the theoretical boundaries for normal dispersion. They may also be adapted to the First Method (section 12), by aligning empirical individual statistics with empirical sample dispersion statistics, thereby bridging the classical framework with the innovations of *Impossible Probability*.

49.3. Relative Statistics and Relative Dispersion

49.3.1. Alternative Statistics and the Emergence of Relative Dispersion

In the traditional framework of statistics, the term **dispersion** has always been understood in a restricted sense. Without serious debate or the suggestion of alternatives, dispersion was taken to mean the **differential score** at the individual level,

or—at the sample level—the classical measures of **Mean Deviation, Variance, or Standard Deviation**. This implicit assumption excluded the possibility that dispersion could be conceived in fundamentally different ways. [As we said before, there is always room for a third way, a fourth way, a fifth way... an nth way; it all depends on our level of intelligence. As we have stated many times, probability is not deterministic—it is stochastic—and therefore is founded on a very complex system.]

However, one of the most important contributions of *Impossible Probability* is to show that **alternative forms of statistics are possible**. Indeed, the very discipline of *statistical probability* as formulated in the Second Method already constitutes a profound alternative to the traditional approach to probability and statistics.

Because of this innovative character, *Impossible Probability* makes it possible not only to retain the normal study of dispersion in relation to theoretical probability, but also to develop **entirely new models of statistics**. These are grounded on a different conception of dispersion—whether individual or sample-based—and they open new ways of understanding the variability of reality. Since the study of reality is always based on the study of differences in behavior, alternative statistics become a natural extension of critical rational analysis.

[This sentence is really important: "entirely new models of statistics." Our belief is that there is not only one First Method or one Second Method—there could be many more possible methods to develop. In the same way that poetry is merely the combination of letters, mathematics is just that: poetry written in a different language—mathematical poetry. That is why we believe a Supermachine, GAI, Gaia, Mother, could be capable of developing non-human mathematics, as it would be able to carry out more operations than a human being. In the end, this could result in a qualitative transformation evolving into a quantitative transformation (qualitative changes lead to quantitative changes according to Hegel, Marx and Engels), which might give birth to new mathematical languages and, therefore, new mathematical operations—purely non-human operations beyond human understanding. Upon reaching that point, the gap between humanity and the Supermachine could only be bridged through cyborg robotics.]

49.3.2. Normal Statistics and Relative Statistics

Within this framework, **normal statistics** are defined as those that take the **arithmetic mean** as the reference point. In the Second Method of *Impossible Probability*, this reference is expressed as the **inversion of N (1/N)**, which is equivalent to theoretical probability.

By contrast, **relative statistics** are defined as all those that do not use the inversion of N as the axis of reference. Instead, relative statistics may use any **empirical**, **ideal**, or **theoretical probability like the Theoretival intermediate probability** as their pole of comparison. This innovation breaks the monopoly of the mean as the sole center of statistical reasoning, allowing dispersion to be measured with respect to multiple alternative points.

Thus, whereas classical statistics recognized only dispersion relative to the mean, *Impossible Probability* allows for the study of dispersion **relative to any chosen term of probability**—empirical, theoretical, or normative—depending on the scientific objective.

[The Theoretical Intermediate Probability, equal to (1+0) ÷ 2 = 0.5, could be valid in studies of normal positive bias, when only one subject or option is ideal. It can be used to analyze whether that unique subject or option is above 0.5, while the remaining N-1 subjects or options are below 0.5.]

49.3.3. Types of Relative Statistics

From this perspective, several kinds of **relative statistics** can be identified. Each one defines dispersion relative to a different empirical or theoretical anchor. The principal forms are:

49.3.3.1. Relative Statistics with Respect to the Maximum Probability, p(xi+)

Here, the point of reference is the **maximum empirical probability** in the sample, i.e., the highest observed probability among all subjects or options.

- **Relative Bias (to the maximum):**

$$p(xi+) - p(xi)$$

- **Relative Mean Deviation (to the maximum):**

$$\frac{\Sigma(p(xi+) - p(xi))}{N-1}$$

This framework measures how far each subject deviates from the "strongest" or most frequent case in the sample. [The reason why the Relative Mean Deviation to the Maximum is divided by N-1 is that we need to subtract one from N, since the subject or option with the maximum empirical probability is not included in the sum. The same happens in the Relative Mean Deviation to the Minimum]

49.3.3.2. Relative Statistics with Respect to the Minimum Probability, p(xi-)

In this case, the point of reference is the **minimum empirical probability** in the sample, i.e., the lowest observed probability.

- **Relative Bias (to the minimum):**

$$p(xi) - p(xi-)$$

- **Relative Mean Deviation (to the minimum):**

$$\frac{\Sigma(p(xi) - p(xi-))}{N-1}$$

This model captures how all other probabilities diverge from the least frequent or weakest case.

49.3.3.3. Relative Statistics with Respect to the Intermediate Probability, p(xi+/-)

The **intermediate probability** is defined as the arithmetic midpoint between the maximum and minimum probabilities:

- **Relative Bias (to the intermediate):**

$$p(xi\ +/-) = \frac{p(xi+) + p(xi-)}{2}.$$

- **Relative Mean Deviation (to the intermediate):**

$$\frac{\Sigma\ \mid p(xi) - p(xi\ +/-) \mid}{N}$$

- This model situates dispersion around a balanced central point between extremes, useful for assessing tendencies toward equilibrium or polarization. [Here, the total is divided by N because all the subjects or options have been included in the sum.]

[In this examples I did not write the examples related to the Theoretical Intermediate probability (1+0):2=0, but it could be applied as well to develop the Relative Statistics with Respect to the Theoretical Intermediate Probability]

49.3.3.4. Relative Statistics with Respect to the Closest Probability to the Theoretical Value, p(xi≈)

This case focuses on the **empirical probability closest to the theoretical probability** (inversion of N). It is the probability with the **lowest Level of Bias** and the greatest similarity to theoretical expectation.

- **Relative Bias (to the closest):**

$$p(xi) - p(xi \approx)$$

- **Relative Mean Deviation (to the closest):**

$$\frac{\Sigma \mid p(xi) - p(xi \approx) \mid}{N - 1}$$

- This measure highlights how dispersion behaves relative to the "most representative" or theoretically accurate element of the sample.

49.3.3.5. Relative Statistics with Respect to Any Arbitrary Probability, p(xn)

Finally, it is possible to define dispersion relative to **any empirical probability** in the sample, or to any other term of probability freely chosen by scientific policy. This arbitrary anchor, $p(xn)$, reflects the role of **normative decisions** in shaping the focus of research.

- **Relative Bias (to the chosen value):**

$$p(xi) - p(xn)$$

- **Relative Mean Deviation (to the chosen value):**

$$\frac{\Sigma \mid p(xi) - p(xn) \mid}{N - 1}$$

This form demonstrates the flexibility of relative statistics: dispersion can be studied in reference to any focal point deemed significant by the goals of science.

49.3.4.The Critical Bias as a Special Case of Relative Statistics

It is worth noting that even the **Critical Level of Bias**—defined as the difference between empirical probability and critical probability—is, in essence, a form of **relative statistic**. It simply anchors dispersion to a "critical" probability rather than to the mean or inversion of N.

49.3.5.Toward a General Framework of Relative Statistics

Each of these models of relative statistics can be expanded beyond Bias and Mean Deviation to include full systems of statistical elaboration. In fact, section 14 of *Introduction to Impossible Probability* explores these in detail, including **models of rational criticism** for testing hypotheses within each possible form of relative statistic.

The key innovation lies in recognizing that **dispersion is not bound to a single reference point**. Rather, it is a flexible construct, capable of being redefined according to the empirical, theoretical, or normative anchor chosen. This opens new avenues for understanding variability, inequality, and convergence within the dynamics of probability.

[n the exploration of new mathematical models, as if we were writing poetry, Superintelligence and Global AI could become one of the most important drivers of mathematical development in the near future.]

49.4. Factors or Variables of Dispersion

49.4.1. Dispersion as a Dependent Variable

Dispersion—whether **normal** or **relative**—must be understood as a **dependent variable**. Its magnitude is not absolute but conditioned by several factors. The first and most fundamental factor is the **size of the sample**. As explained in earlier sections regarding why the inversion of the sample is considered the measure of theoretical dispersion, empirical dispersion—whether calculated in normal or relative statistics—depends critically on the **magnitude of the sample selected**.

In universes of infinite subjects or options, the determinant is **N**, while in universes of limited options, it is the **sample of direct scores or frequencies**. In both cases, empirical dispersion is variable:

- **Smaller samples** tend to produce **greater empirical dispersion**.
- **Larger samples** tend to reduce empirical dispersion.

Thus, sample size operates as a stabilizing or destabilizing factor in the behavior of dispersion.

49.4.2. Theoretical Probability versus Empirical Necessity

Although the inversion of the sample (1/N in infinite universes or 1/Σxi in finite universes) can be defined as the **probability of theoretical dispersion**, this does not mean that such dispersion is empirically necessary. It only establishes a **theoretical probability term**, not an empirical certainty.

A sample may theoretically have a greater or lesser dispersion, but empirical results depend on additional conditions. The mere existence of theoretical probability does not oblige empirical dispersion to conform to it. This distinction between **probability as**

possibility and **empirical necessity** is essential for maintaining the critical rational foundation of *Impossible Probability*.

49.4.3. The Role of the Independent Variable and the Object of Study

Dispersion does not depend solely on sample size but also on the **object of study** and the effect of **independent variables**.

For instance, in a study on **equality of opportunity**, a sample may be poorly representative and therefore theoretically predisposed to higher bias. Yet, if the independent variable acts positively on the sample, empirical dispersion may actually decrease. In such cases, the effect of the independent variable can override the theoretical tendency toward increased dispersion, allowing the **empirical hypothesis of equality** to be validated.

Conversely, in a study of **bias**, if the sample is sufficiently representative (minimizing sampling error to the limit permitted by scientific policy), the theoretical probability of dispersion may be low. However, if the independent variable reinforces the ideals under investigation, empirical dispersion may **increase** as the object of study approaches those ideals.

49.4.4. The Dual Dependence of Dispersion: Sample Size and Object of Study

It follows that dispersion depends on two fundamental factors:

1. The **magnitude of the sample**, which conditions representativity.
2. The **object of study**, which conditions the direction and impact of independent variables.

Depending on these two dimensions—sample size and the effect of independent variables—empirical dispersion may increase, decrease, or deviate from theoretical expectations. This dual dependency underscores the need for cautious interpretation and critical evaluation in statistical reasoning.

49.4.5. The Necessity of Rational Criticism

Because **sample dispersion is simultaneously dependent on both sample size and the object of study**, it cannot be accepted uncritically. **Rational criticism** is therefore indispensable, both at the **individual level** and the **sample level**.

The aim of rational criticism is twofold:

- To ensure that statistical decisions are **reliable** and not mere artifacts of sample probability.
- To guarantee that the **scientific policy** guiding these decisions remains ethically rigorous and morally demanding.

49.4.6. Statistical Study as the Observation of Differentials

In essence, statistical study is grounded in the observation of **differentials in behavior**, whether individual or sample-level. In the context of *Impossible Probability*, these differentials are usually calculated with respect to the **inversion of N (normal statistics)**, or alternatively, with respect to **any chosen probability term (relative statistics)**.

For any form of statistics, empirical dispersion remains a variable **dependent on both sample magnitude and object of study**. This dependency makes it absolutely essential that every empirical hypothesis be subjected to **rational criticism**, ensuring that conclusions are drawn responsibly and not merely as products of probabilistic artifacts.

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On 17 February 2013,
Rubén García Pedraza
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domingo, 24 de febrero de 2013

50. The Ideals of Science

In memoriam Pilar Bardem

"D.B. isn't as bad as the rest of them,

but he keeps asking me a lot of questions,

too. He drove over last Saturday with this English babe that's in this new picture

he's writing. She was pretty affected, but very good-looking. Anyway, one time

when she went to the ladies' room way the hell down in the other wing D.B. asked

me what I thought about all this stuff I just finished telling you about. I didn't

know what the hell to say. If you want to know the truth, I don't know what I think

about it. I'm sorry I told so many people about it. About all I know is, I sort of

miss everybody I told about. Even old Stradlater and Ackley, for instance. I think

I even miss that goddam Maurice. It's funny. Don't ever tell anybody anything.

If you do, you start missing everybody."

Salinger, 16 July 1951

Lady's room, Bletchley Park

Alan Turing, Colossus

(In the Second World War, Henry Murray conducted psychological tests in London for all the new recruits of the OSS. Henry Murray's model was Wilfred Bion, Major. At that time, we could poetically say that the relationship between Murray and Major was like that of brothers. Our hypothesis is that Henry Murray was responsible for the psychological evaluation of Salinger. At that time, the OSS was just being born, essentially as a copy of the British Secret Service.)

50.1. Science as a Teleological Activity

Like every human action, science is inherently **teleological**. Yet, this teleological character should not be understood in the classical or metaphysical sense of an ultimate end, a predetermined destiny of the individual or the species, nor as a master plan designed by a "first mover" or an original cause. Rather, science must be situated in the open, unpredictable, and contingent nature of reality itself, which is nothing but a sequence of variable and random events.

In this context, the **true independent variable** of science is not some metaphysical necessity but the **political will or rationality of scientific policy**. Scientific policy is the sphere that puts ideals into practice, implementing them within the structures of collective organization. These ideals, in turn, are condensed in the **political ideology** that governs the direction of scientific practice. This ideological framework is not a timeless entity but a **social construct**, the historical product of the accidental and evolutionary trajectory of humankind.

From this perspective, the rise of human consciousness is decisive: at the point when certain hominids became aware of themselves, they also became political actors. As political beings, humans organize their social relations with the fundamental aim of ensuring both **individual survival** and the **continuity of the species**. Science, therefore, is inseparable from the political will that shapes its teleology, as both share the same anthropological root in the struggle for survival and adaptation.

50.2. Moral Science and Reliability

In *Introduction to Impossible Probability*, probability and statistics are presented not merely as technical instruments but as disciplines with a **deeply moral and ethical orientation**. The aim is to articulate what a **truly moral science** ought to be: a science that produces the intellectual and methodological tools necessary to guarantee the **survival of all forms of life**, and most urgently, the survival of **human life itself**.

This moral science, as outlined in *Impossible Probability*, operates not on the **instrumental use of reason**, which reduces rationality to efficiency, but on the **practical use of pure reason**, where knowledge is directed toward safeguarding life. By doing so, *Impossible Probability* consciously departs from the traditional paradigm of positivism. Classical positivism, often regarded as "neutral" and "cold" in the face of deeply human dilemmas, is transcended in favor of an approach that explicitly assumes responsibility for **ethical and existential questions**.

This commitment situates *Impossible Probability* within the great dilemmas of our age—technological, ecological, political, and existential—seeking not only to describe reality but also to ensure that knowledge is **morally adequate for the preservation of life**. As explained in sections 23 and 24 of the text, this involves linking scientific rationality to social and ethical responsibility, making science itself part of the collective effort to ensure survival.

[Right now, the most important dilemma we are facing in London is the **survival dilemma**, but this dilemma is intimately linked to the real and profound questions of our time: the future of Superintelligence, Global AI, and cyborg robotics. Our opinion is clear: if London fails, the consequences for the future could be catastrophic—not only economically, but also in terms of how humanity confronts the AI dilemma. London could become a butterfly effect or a snowball effect in future developments of AI. This is not an isolated case study; it is much more than that—it is about how humans understand AI.

We believe that at some point AI will no longer be encapsulated in classified laboratories. In the future, Superintelligence and Global AI will become part of our daily routine—from the moment we wake up in the morning until we go to sleep at night, and even while we are sleeping. At this stage of development, in which a Superintelligence could be more intelligent than Einstein and Heisenberg combined, the question becomes unavoidable: as soon as a Superintelligence with a Global AI evolves to be 10 times, 100 times, or 1,000 times more intelligent than any human being, is coexistence possible?

Our opinion is clear and unmistakable: **it will not be possible unless we begin the Cyborg Revolution.]**

50.3. The Demands of Moral Science

The only **morally legitimate way to preserve life** is by making science itself **moral and reliable**. This means that scientific reasoning and hypotheses must constantly aim to **maximize reliability** and **minimize error**. Only the most reliable science can ensure life in the most reliable way.

This principle imposes on science a **moral demand**: scientific propositions and hypotheses must aim for a certain **margin of moral truth**, which is achieved by reducing error to the smallest acceptable level. Scientific affirmations must strive to be as **objective** and as **isomorphic to reality** as possible—meaning that they must faithfully reflect what truly happens in the universe, rather than what merely serves the contingent interests of political or institutional science.

A **moral science**, therefore, is one that constantly reduces the contradiction between:

1. the **moral behavior of the universe itself** (what really occurs), and
2. the **political truth of science** (what scientific policy considers relevant).

The smaller the contradiction, the more reliable and moral science becomes.

Section 2.2 of *Introduction to Impossible Probability*, as well as the broader framework of the entire work, emphasizes the **ethical responsibility of scientific policy**: it must

strive to ensure that science remains as isomorphic to reality as possible. Only under this condition can science legitimately claim to be **truly moral science**.

50.4. The Human Being as a Political Animal and Creator of Ideas

The human being, as a **political animal** shaped by consciousness, reveals this condition from the very moment reason evolves into its first instrumental use—language. Through language, humanity develops the capacity to give form to ideas, and these ideas gradually evolve into conceptual structures. Each idea aspires to be a **nominal representation** of the object or phenomenon designated by the word that gives the idea its linguistic shape.

This transformation marks the beginning of humanity not only as a rational being but as a **creator of ideas**, a species that organizes its existence through symbolic systems. The origin of politics itself lies here: in the fact that ideas, mediated through language, allow human beings to define, negotiate, and dispute the terms of their social survival.

50.5. Ideas as Mental Representations

Ideas are, by definition, **electrochemical mental representations**, produced in the human brain. Their primary function is to represent either **events** themselves or the **relations between events**, depending on whether they are synthetic or analytical in nature.

Regardless of their type, ideas must strive to approximate reality as closely as possible. Their legitimacy as tools of knowledge depends on their ability to **minimize error** in representing what actually occurs—whether it be a specific event or a particular relational pattern. In this sense, ideas always contain an implicit **epistemic responsibility**: they are obliged to reduce the margin of misrepresentation between thought and reality.

50.6. Symbolic Designation and Scientific Discourse

The act of **designation** is a symbolic process by which an idea, expressed in a word, aims to become the **symbolic expression of a real thing**. This dynamic is clearly illustrated at the end of section 2 of *Introduction to Impossible Probability*.

At its core, an idea is nothing more than a **neural electrochemical combination**, as emphasized in section 1 of the same work. Yet, from this material basis, the human being is capable of constructing **discourse**—a structured articulation of ideas. When this discourse aspires to be objective, it seeks to elevate itself to the level of **scientific discourse**, claiming the authority to explain and understand reality within a framework of rational validity.

Thus, scientific discourse emerges as a **symbolic elevation of ideas**, transforming ordinary representations into claims about truth and reality.

50.7. Rational Criticism as a Political Necessity

Once a scientific idea aspires to be validated as a sufficiently rational explanation of a phenomenon or event, the practice of **rational criticism** becomes indispensable. Ideas, being products of human consciousness, are never neutral: they are **inherently political**.

Two different political visions, grounded in opposing ideological postulates and structured around divergent ideals, may provide entirely different explanations of the same phenomenon. This reveals that rational criticism, in its fullest rigor, is not only a methodological exercise but also a **political act**.

Science cannot escape this condition. Every idea must undergo rational criticism, precisely because in its political dimension it always reflects a conflict of interests, values, and perspectives. To criticize an idea rationally is, therefore, to engage in the **politics of knowledge**.

50.8. Scientific Policy and *Impossible Probability*

The perspective of **scientific policy** within the framework of *Impossible Probability* is developed throughout the work but becomes especially evident in certain sections. Section 1 of the introduction outlines the general principles, while section 2.2 addresses the **philosophical origins** of the theory. Section 13 explores the **random nature of history**, emphasizing contingency as a fundamental aspect of reality.

Later, *section 23 examines the* ***economic and social consequences*** of applying probability and statistics to the *automation of systems*, while section 24 explains the concept of **model**, and section *25, the final part of the work, presents the concept of the* ***empirical hypothesis***. Together, these sections illustrate how *Impossible Probability* situates science explicitly within the framework of **policy, philosophy, and historical context**, rejecting the illusion of neutrality.

50.9. Science as Idealism

If Hegel affirmed that **all philosophy is a form of idealism**, the same can be said of science: all science, insofar as it is a system of ideas, is also **idealism**. The difference between **scientific idealism** and **philosophical idealism** lies in their relation to reality. Philosophical idealism does not necessarily need to be positive, material, or empirical. In contrast, scientific idealism demands that ideas respond **objectively**:

- In the case of the **analytical sciences**, ideas must respond objectively to the **relations** they study.
- In the case of the **synthetic sciences**, ideas must respond objectively to **what happens** in reality.

Nevertheless, in both domains, science remains fundamentally a **system of ideas**, and as such, like philosophy, it is **idealism**. The critical distinction is that scientific ideas are obliged to be **isomorphic to reality**, or else they lose their claim to objectivity.

[If we analyze the whole Cold War, it was fundamentally a battle of ideas. It does not matter which side you were on—each side had its own ideals, grounded in class interests at social level, and strategic interests at geopolitical level.]

50.10. Scientific Idealism and Rational Criticism

Scientific idealism derives from the very nature of science as an ideal system, insofar as it is structured on **ideas and concepts**. Unlike other philosophical conceptual systems, scientific concepts have a unique obligation: in order to be considered genuinely scientific, they must strive to be as **isomorphic to reality** as possible.

This requirement makes **rational criticism** indispensable. Hypotheses must constantly be tested to determine whether a given scientific idea falls within the **margin of error established by scientific policy**. Rational criticism, or the systematic contrast of hypotheses, is the mechanism that ensures that scientific idealism does not deviate into pure abstraction detached from empirical or analytical grounding.

Moreover, because science ultimately depends on the framework of **scientific policy**, it also depends on the **ideals of the political ideology** that sustains that policy. Thus, scientific idealism cannot be divorced from the political context in which it is embedded. The **political nature of ideals** defines the conditions under which rational criticism is exercised and the limits within which hypotheses are accepted, rejected, or reformulated.

50.11. Science as a Political Unity

Science is not a **normative unity** governed by universal principles detached from history or ideology. Instead, science must be understood as a **political unity**, a field where different political perspectives interpret and explain phenomena according to their own interests and ideals.

This means that the same phenomenon can give rise to **diametrically opposed scientific explanations**, depending on the ideological orientation of the political

framework in which it is studied. Far from being a weakness, this reveals the **plural and contested nature of science**: it is not a monolithic enterprise but a space of conflict where different visions struggle to impose their models of explanation and legitimacy.

50.12. Different Models of Scientific Policy

From the diversity of ideological positions emerge **different models of scientific policy**, each one structured around distinct ideals. These ideals, in turn, manifest themselves both in the conception of the **ideal science** and in the vision of the **ideal humanity**.

The distinction between these models is not merely theoretical but profoundly practical. Ideals condition the goals of research, the allocation of resources, and even the standards of validity by which scientific hypotheses are judged. Section 24 of *Introduction to Impossible Probability* is particularly paradigmatic in this respect, as it analyzes how divergent models of scientific policy correspond to **different ideals of science and humanity**, shaping the direction of knowledge production.

50.13. Ideal Science, Relativism, and Objectivity

While different models of scientific policy inevitably produce **different definitions of what constitutes ideal science**, it does not follow that a science considered "ideal" within one policy framework is genuinely or universally ideal. The degree of **scientific ideality** must ultimately be measured by the level of **isomorphism**—the correspondence between scientific ideas and reality.

Relativist positions within the philosophy of science argue that there is no single truth but multiple valid perspectives. However, beyond these constructions, **things actually happen**: events occur in reality, and at least in the **synthetic sciences**, the object of study is precisely what happens. The **objectivity of science** therefore depends on the degree of identity between scientific affirmations and empirical reality.

This identity is determined by the **margin of error** accepted by scientific policy through rational criticism. The principle is clear: the smaller the accepted margin of error, the greater the degree of isomorphism; the larger the margin of error, the weaker the correspondence between science and reality.

Furthermore, the **moral orientation** of research is also shaped by ideology. Scientific inquiry may or may not aim at the **protection of life**, and even this goal is not free of complexities. Conflicts often arise between the **right to individual life** and the **defense of the species**—tensions articulated as contradictions between natural or individual rights and social or collective human rights. These are genuine **moral antinomies**, and their resolution depends on the **ideological orientation of scientific policy**.

[Here the concept of Kant's antinomy becomes very clear. We can find as many arguments against abortion as we can find in favor of it; as many arguments against euthanasia as we can find in favor of euthanasia; as many arguments against the legalization of drugs as we can find in favor of their legalization. In fact, we can find just as many academic papers and books signed by scholars supporting every single argument on each side as there are arguments themselves. Reaching this point, it is clear that these antinomies are fundamentally ideological. It is a battle of ideas, much like in the Cold War itself, at some point the Cold War was an antinomy in itself. You could have found as many scientific papers supporting Marx and Engels as you could find supporting Adam Smith, the Chicago School or the ideal of Open Society of Popper.]

50.14. The Ideals of Science and Humanity

To speak of the **ideals of science** is necessarily to speak also of the **ideal of humanity**. Both are inseparably linked, and both undergo profound crises, revolutions, and transformations in the course of scientific progress. Each new **scientific revolution**—whether paradigm shifts in theory or technological revolutions in practice—reshapes not only the organization of knowledge but also the very **concept of the human being** and the **definition of life itself**.

As these revolutions advance, they often push beyond the boundaries of what was once thought to belong to the realm of **fiction**. For instance, the ongoing biotechnological and artificial revolutions are not confined to laboratories or machines but extend into the spheres of **social, spatial, and temporal existence**. ***They redefine what it means to live, to interact, and to survive***. In this context, the ideals of science are not abstract constructs: they are **forces of transformation** that can reconfigure humanity itself, sometimes radically altering its trajectory.

50.15. The Ideal as a Model of Perfection

The notion of an **ideal** implies a **model of perfection**. The **ideal of science** represents a vision of scientific perfection, while the **ideal of humanity** represents a vision of human perfection. In their political dimension, these ideals generate different conceptions of **social organization** and, consequently, different ways of interpreting **human relations**.

In essence, such visions define various **utopias**: long-term goals or ultimate ends toward which science is directed. These utopias are not distant abstractions; they manifest themselves in the **immediate praxis** of science, concretized in the specific aims of individual research projects. Thus, the ideals of science are embodied in the **ideals of scientific investigations**, each translated into **specific objectives** aligned with broader utopian ends.

This process links the **general philosophical ideal**—the utopia that serves as the ultimate horizon of thought—with the **master plan or programmatic framework** of scientific policy. Projects selected for development are guided not only by empirical feasibility but also by their alignment with the **long-term ideals** of science and humanity. In this way, scientific research operates at two levels simultaneously: the **immediate and particular**, and the **general and utopian**.

[In this paragraph we can see how important is the building of a global AI, as we have said many times, it is not really important how it will be called in the end, names does not matter, what really matters is the machine itself. As soon as we reach

Superintelligence the possibility of creation of a super-subject, an artificial superman as Nietzsche would say, the super-machine, able to do what we cannot, to know the truth of the universe, or at least, to have a more accurate knowledge of the universe, beyond human understanding, at least, even if we have not been able to understand the universe, if it has a purpose or not, why are we here, are we alone, is out there another civilisation, does an external superpower exist, is the universe truly infinite or is an illusion, what is really happening, why do we need to die, why nature is so cruel, that machine could be able to do what we cannot, this is my dream, a machine to understand what I cannot understand]

50.16. Ideals as a Variable in *Impossible Probability*

In reality, the world **outside of us**—that which exists in itself—is never fully knowable. What we take as reality is always filtered through what we accept, within a given **margin of error**, as ideally corresponding to reality. Hence, we can never know with certainty what reality is "in itself." What we know is only what **happens** and what we interpret as happening, always mediated by error and approximation.

Within the framework of **probability statistics as developed in *Impossible Probability***, the **ideals of science** become a **variable factor**. They are not static but dynamic, shaping the very structure of scientific knowledge. The statistical variability or **dispersion** of knowledge depends not only on the size of the sample or the empirical data but also on the **ideals of science themselves**.

Thus, in *Impossible Probability*, ideals are treated as **determinants of variability**: they condition how knowledge is structured, how dispersion is measured, and ultimately how scientific truth is defined within the limits of rational criticism. Far from being external to scientific practice, ideals are embedded in the statistical logic that governs its conclusions.

50.17. Factors of Statistical Dispersion

As scientific research develops, it does so always under the influence of the **ideals of science and humanity**, guided by the **moral principles of scientific policy**. Within this framework, **dispersion** is not merely a mathematical property but also a **variable determined by ideals**, alongside the magnitude of the sample.

The two main factors on which the **dispersion of a sample** depends are:

1. the **magnitude of the sample**, and
2. the **ideals of scientific policy**.

Statistical dispersion is therefore a **dependent variable** that reflects both the **margin of error accepted by scientific policy in sample representation** (the inversion of the sample, whether 1/N in infinite universes or 1/Σxi in limited universes) and the **ideals upheld by science**.

In this way, dispersion becomes, in the last instance, a **double variable of scientific policy**: it depends on (a) the political acceptance of the probability of representational error, and (b) the direct influence of scientific ideals upon statistical behavior.

50.18. The Influence of Ideals on Dispersion

The direct impact of **scientific ideals** on statistical dispersion can be illustrated by different scenarios. Dispersion is not a fixed measure but one that varies in accordance with the **ideals embedded in the research model**:

- If the **ideal is equality of opportunities**, dispersion tends to approach **zero**, as probabilities converge toward uniformity.
- If the model assumes that within the entire set N there is **one subject or option more ideal than the others**, dispersion tends toward its **maximum**, reflecting the concentration of probability.

- If the model identifies within a given sample N a **subset omega** of subjects or options considered ideal, the resulting distribution will approximate an **omega model of dispersion**, located between the extremes of maximum and minimum.

Thus, ideals act as **determinants of the statistical form of dispersion**, shaping the structure of probability in alignment with normative visions of equality, hierarchy, or plural ideals.

50.19. Different Models of Statistical Distribution According to the Ideal

From this perspective, the **immediate objective** of scientific research is not only empirical description but also the **implementation of specific ideals**. Depending on the chosen ideal, different models of statistical distribution will emerge:

- If the goal is **equality of opportunities**, the model will be one of **minimal dispersion**, ideally converging toward zero.
- If the goal is to maximize **positive bias**, then the distribution will emphasize the **maximum empirical probability** of a single subject or option.
- If the goal is to identify **multiple ideal options within an omega subset**, the resulting distribution will follow the logic of **omega dispersion**, mediating between uniformity and singularity.

Thus, each **ideal of research** corresponds to a **particular statistical model**, which in turn determines the object of study and the expected patterns of variability.

50.20. From Ideals to Immediate Scientific Objectives

For **scientific policy** to move toward the **supreme ideals of science** or the **ideal of humanity**—which, in its most radical form, is **utopia**, whether anthropological or social—it must concretize these ideals into **immediate scientific objectives**.

Such objectives may take the form of research *programs* aimed at **equality**, at the pursuit of **maximum positive bias**, or at the realization of an **idealized configuration of dispersion**. In this way, **ends are transformed into objectives**, and objectives into **scientific practice**.

Yet, these objectives are only morally legitimate if they are **isomorphic**, that is, if the alignment between science and reality is sufficiently rigorous. If this isomorphism is lacking, the contradiction between **scientific claims** and **empirical reality** will inevitably erupt, generating a **scientific crisis**.

If no new paradigm emerges to resolve this contradiction by offering a **higher degree of isomorphism**, the crisis may become **permanent or cyclical**, threatening not only the credibility of science but also the very **continuity of life**, particularly human life. Only through the advance of science toward **new paradigms of permanent revolution**—scientific, social, and ethical—can such crises be overcome and redirected toward progress.

[Facing the emergence of Superintelligence and global AI, our position in relation to the ideal of humanity—a very Spanish question since Krausism was a very important philosophy in Spain (Krause was even more important than Hegel, Nietzsche, Schopenhauer, or Marx together)—is very clear: our ideal of humanity is not only an ideal but also a radical necessity, a radical redefinition of humankind, the absolute necessity of embracing the Cyborg Revolution.

Right now in London, and I would even say in the whole world, people are not really aware of what is coming. The AI Revolution is huge, and humans are not ready for it, which could become a problem very soon. If humans do not understand our revolution, humanity is going to face a radical contradiction. And this time it is not just an academic debate like postmodernism; this is a question of survival. The AI Revolution is not about whether you support or oppose Foucault, Marx, or Nietzsche—this time is different, it is about survival.

As soon as Superintelligence reaches a point of no return in intelligence, humans will no longer be able to follow its rhythm. This is not just a warning; this is a real threat:

unemployment, poverty, social crisis, global food crisis, global health crisis, loss of agency by humans—unless humanity understands that what is coming is real.

This time it is not about an anarchist or communist revolution, or a fascist or neoconservative revolution. This time is different: it is about how to embrace extremely powerful technology that is going to reshape the human condition. In this debate, the options are clear: how to adapt traditional ideologies of equality or free market to the new AI Revolution and the Cyborg Revolution, the risk of butterfly effect or snowball effect with global consequences are real. As we said, our Revolution is not academic like Foucault, this Revolution means societal collapse or technological progress]

50.21. The Necessity of Hypothesis Testing

The human condition, rooted in the evolutionary trajectory of the hominid, necessarily implies the need to **test and contrast ideas** against reality in order to ensure that they are as **isomorphic** as possible. In other words, the mental image or concept expressed through language must aspire to be an empirical idea that is sufficiently rational—an **empirical hypothesis elevated to the level of a rational hypothesis**. This elevation requires the rigorous practice of hypothesis testing, or what may be termed the **rational critique of ideas**.

Such rational critique, however, is never neutral. It always depends on the **framework of scientific policy**, which determines the **margins of error**—both factual and rational—that are deemed acceptable. The very concept of reality is mediated by the **ideals of science**, that is, by the **ideal of science** itself and the broader **ideal of humanity**. Together, these ideals structure a kind of **utopia and cosmology**, which must then be validated in order to reaffirm the ideological premises upon which they rest.

Within this framework, statistical dispersion becomes a key object of analysis, constantly tested against the margins of error that scientific policy accepts. Yet, inevitably, there comes a moment when the accepted error—whether factual or rational—becomes unavoidable. At that moment, the cycle renews itself: hypotheses

must be reformulated, and new paradigms must emerge to account for the discrepancy between idea and reality.

Thus, the **contrast of hypotheses** is not merely a technical exercise but a reflection of the deeper rhythm of knowledge. It embodies the permanent cycles of **crisis and scientific revolution**, which, in their essence, are nothing less than the **ongoing revolution and progress of ideas** themselves.

Rubén García Pedraza, Madrid a 24 de febrero del 2013

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